Modelling Financial Market based on Econometric and Complex Network Analysis

Thesis submitted in accordance with the requirements of
the University of Liverpool for the degree of Doctor in Philosophy by

Yanhua Chen

Supervised By
Dr. Athanasios A. Pantelous
Dr. Konstantin M. Zuev

Institution of Risk and Uncertainty
School of Engineering
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Abstract

The complex network theory, especially, the economic and financial networks have offered a new approach that emphasizes the complexities and interdependencies in the financial market. In this thesis, I am interested in combining the complex network theory and econometric measures, namely, cointegration and error correction models (ECM) to reveal the internal connectedness structure of the financial market and their dynamic characteristics evolution over time.

The initial Chapters 1–2 present an introduction, background knowledge as well as the methodology has been applied throughout the thesis. Chapters 3–5 introduce corresponding specific problems leading up to their solutions. Specifically, in Chapter 3, we examine the dynamic evolution of short-term correlation, long-term cointegration and ECM-based long-term Granger causality between each pair of US, UK, and Eurozone stock markets from 1980 to 2015 using the rolling-window technique. A comparative analysis of pairwise dynamic integration and causality of stock markets, measured in common and domestic currency terms, is conducted to evaluate comprehensively how exchange rate fluctuations affect the time-varying integration among the S&P 500, FTSE 100 and EURO STOXX 50 indices. Chapter 4 seeks to incorporate the long-run cointegration and short-run error correction mechanisms to build up the financial networks to quantify the connectedness across 46 stock markets worldwide from January 2007 to June 2017. By constructing the static ECM-based global stock market network, the topological structure reflects the regional integrated and segmented stock markets. The dynamic international stock market further reveals the time-varying properties of both error correction effects and long-run equilibrium relations amongst 46 stock markets during periods of financial turmoil and implementation of the QEs in the Fed, BoE, BoJ, and ECB, respectively. In Chapter 5, we analyze the financial effects of Brexit-vote on the stocks traded on the London Stock Exchange (FTSE 100 and FTSE Mid250 Index). Specifically, we construct corresponding British stock networks using the ECM models to investigate the short-run self-correction mechanisms as well as long-run equilibrium amongst stocks from sectoral-level before and after the Brexit-vote. To extract most strongly related interactions from the British stock networks, the minimal spanning tree (MST) and hierarchical clustering analysis are applied for filtering network and to detect the taxonomy and hierarchical topological structure based our proposed Jaccard distance metric. Each chapter is followed by a mini-conclusion. In the end, we summarize our results and conclude the thesis by presenting some research directions based on our findings in Chapter 6.

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Notations

The following notations and abbreviations are found throughout this thesis:

ADF	Augmented Dickey-Fuller test
BH	Benjamini and Hochberg procedure
BoE	Bank of England
BoJ	Bank of Japan
CAS	Complex Adaptive System
DF	Dickey-Fuller test
ECB	European Central Bank
ECM	Error Correction Model
ECT	Error Correction Term
EEA	European conomic Area
EMH	Efficient Market Hypothesis
EU	European Union
FDR	False Discovery Rate
Fed	Federal Reserve
LSE	London Stock Exchange
MST	Minimal Spanning Tree
PDF	Probability Density Function
PIIGS	Portugal, Italy, Ireland, Greece and Spain
PP	Phillips-Perron test
QE	Quantitative Easing
QQE	Quantitative and Qualitative Easing
VAR	Vector Auto-regression
VECM	Vector Error Correction Model

Chapter 1

Introduction

1.1 Financial Networks based on Econometric Measures

Understanding and analyzing the complexity of the financial market has taken on a critically important role to explain systemic risk as well as maintaining financial stability over the past few decades. There is a considerable number of heterogeneous interacting agents have been identified in the financial market, leading to complex interactions influencing its behaviors. This led to another school of thought that considers the financial market as a complex system to interpret its complexity [1, 2]. Yet the recent advances in network science theory encouraged researchers to apply this framework to replace traditional statistical methods with network-based measures. Especially, the economic and financial networks have offered a new approach that emphasizes the complexities, internal connectedness structure and dynamic characteristics evolution of cross-border financial markets [3].

Correlation-based measures remain widespread to characterize the financial market as a complex network in the last few years [4–7]. While the financial literature recently became interested in combining network-based approach and econometric tools to shed some light on the connectedness of asset returns and systemic risk issues in the financial market [8–13]. Particularly, the influential study of Billio [8] successfully used the Granger-causality models to build up financial networks for understanding the short-run directional causal connectedness among financial institutions. Under the framework of vector-autoregressive (VAR) models, Diebold and Yilmaz [9, 10] defined the directed and weighted spillover network using forecast error variance decomposition (VDA) to explain volatility spillover among asset returns. Extending their work, Alter and Beyer [11] derived the impulse responses (IRs) from the VAR models with exogenous variables to construct the spillover network and analyze the dynamics of spillover effects in the financial market. However, a change in one financial asset returns might affect another asset returns immediately, i.e., in the short term, or the effect may be delayed, occurring the future across several time periods, i.e., in the long run. Whilst these studies mainly focus on how to correctly identify the instantaneous effects between asset returns. As a consequence, little consideration of the possibility that the long-run effects between asset prices from the perspective of econometric and network approach.

The importance of the distinction between the short-term and the long-term effects amongst financial assets became evident even earlier with the dawn of cointegration theory [14]. In particular, an error correction model (ECM) or its multivariate version, the vector error correction model (VECM), which highlights that using historical asset prices and asset returns is preferable to using just asset returns since the former include both the long-run and the short-run information, while the latter only contains the short-run information [14–16]. Therefore we aim to contribute to the literature bringing together ideas from network theory, cointegration, and ECM models to capture not only the short-run instantaneously effects, but also validates the long-run equilibrium relationships amongst financial assets.

On the other hand, deviations from the long-run equilibrium value of the spread might happen as a result of a shock in financial market volatility. However, due to investors' tastes and preferences, market forces and government regulations will bring the short-run deviations between stock markets back to their long-run equilibrium linkages [17]. Such a model is called an ECM model because it reflects a self-regulating mechanism that could automatically correct the short-run departures from the long-run equilibrium among asset prices [18]. Yet there is still no literature report the short-run error correction mechanisms in the financial market from the network science perspective. Motivated by the absence of empirical evidence, in this thesis one other contribute is to draw on econometrics and network analysis to explore the short-run error adjustment effects in the financial market. In particular, we want to know whether such error correction mechanisms between financial assets are time-varying and if so what the difference according to the state of the economy, i.e. in boom and bust phases.

1.2 Financial Shocks and Quantitative Easing

Since financial crises could lead to dramatic changes in investment behaviors, market fundamental and economic policies worldwide, it is essential to study the short-run deviation adjustment effects and long-run cointegration patterns between financial assets during different phases of the financial turmoil. Specifically, the severe tensions that arose in the international financial market in August 2007 due to the US sub-prime crisis have dramatically influenced the global economy. Then the following collapse of Lehman Brothers in September 2008 sparked a global financial crisis that affected the real sector and caused a rapid, synchronized deterioration in most major economies worldwide [19]. It turned into a sovereign debt crisis in the European and reached new heights during the summer of 2011 associated with Standard and Poors (S&P) announced that America's credit rating would be downgraded from AAA to AA+. Eventually, it triggered a sharp drop in stock prices in stock exchanges across the United States, Middle East, Europe and Asia.

In the wake of the US Great Recession of 2007–09 and the outbreak of the following crisis in the Euro-Area, the US Federal Reserve (Fed), along with the Bank of England (BoE), Bank of Japan (BoJ) and European Central Bank (ECB) respectively announced and implemented a series unconventional monetary policies (UMP), which are commonly known as Quantitative Easing (QE) programmes to bolster weak asset markets, as well as to stimulate the real economy [20]. A general feature of the existing literature has been verified that episodes relating unconventional monetary policies could have influenced in the stock markets to some extent [21–23]. Yet such studies provide few insights about the effects of the occurrence of QE activity and the intensity of that activity on the patterns of linkages amongst stock markets in the context of the fiscal policy shock. Therefore, in this thesis, we further assess potential differences and/or similarities in adjustment velocity towards the long-run equilibrium trend between stock markets worldwide during the different implementation phases of QEs.

Further, on June 23, 2016, the British government officially announced that the United Kingdom voted to leave the European Union, what is commonly known as "Brexit". One significant impact of this political and financial uncertainty is that the UK Sterling weakened sharply and remained substantially below its pre-Brexit level [24]. However, in the UK stock market, the FTSE 100 index did not fall as much as the mid-cap FTSE 250 index after the Brexit vote, since roughly 70% of revenue made by the companies from FTSE 100 index is generated abroad and benefiting from the weaker pound. In particular, the shares of companies with more foreign sales suffered less from the announcement of the Brexit referendum [25]. Such financial uncertainty triggered by the political events also arise our interests to detect its influence on the domestic financial market as well as the global market.

1.3 Contributions of the Thesis

Owing to the background above, this thesis contributes to the extant literature on studying the differences and similarities between the short-term correlation, long-term cointegration and ECM-based long-term Granger causality between each pair of the US, UK, and Eurozone stock markets in Chapter 3. Especially, using a dynamic framework that considers the various economic, financial and political shocks in the economy over 1980–2015 gives us the opportunity to compare the levels of correlation and cointegration relations during episodes of financial distress over different periods. Further, a comparative analysis of pairwise dynamic integration and causality of stock markets, measured in common and domestic currency terms, is conducted to evaluate comprehensively how exchange rate fluctuations affect the time-varying integration among the S&P 500, FTSE 100 and EURO STOXX 50 indices.

More importantly, we attempt to combine the complex network theory and econometric measures to build up the ECM-based financial networks in Chapter 4 and Chapter

5 to explore the short-run error adjustment effects and long-run equilibrium in the financial market. To the best of our knowledge, our study is among the first to examine such interactions amongst financial asset prices through the econometrics and network approach.

To specify, the static and dynamic global stock market networks are built up based on the ECM models in Chapter 4 to detect the heterogeneity and systemic risk of the international financial market. Besides, our investigated dynamic network metrics (namely, average network strength and degree, network density, clustering coefficient, reciprocity, and average path length) together can be served as a good risk indicator to reflect both tranquil and turmoil periods of the international stock market over January 2007–June 2017. Through mapping the dynamic network structure of the international stock market using the ECM models, the time-varying number of cointegration relations among 46 national stock markets could be identified, and the estimated error correction coefficients could further reflect the time-varying self-regulating adjustment to disequilibrium of each stock market over time. Finally, another contribution of in Chapter 4 is to explore the potential differences and/or similarities in dynamic equilibrium self-adjustment effects of stock markets in the US, UK, Japan, and "PIIGS" countries (i.e., Portugal, Italy, Ireland, Greece and Spain) during phases of financial turmoil and QEs implementation. This will enable us to see of the financial crises and QE have common effects on, or whether each phase had distinct effects.

To reduce the complexity of the ECM-based financial networks, the minimal spanning tree (MST) is employed for network filtering and to extract the strongly related connections in the British stock network before and after the Brexit-vote in Chapter 5. As it is well known that to analyze the topological MST structure of the stock market, a distance metric is needed to define. Since Mantegna [4] proposed a distance function based on Pearson correlation coefficients between pairwise financial asset returns, it has been used in a considerable number of works for constructing MSTs to analyze the complex structure of the financial market [5, 7, 26–28]. While, unlike these studies, our proposed Jaccard distance metric that evaluated from the directed and weighted ECM-based stock network is another contribution in Chapter 5.

1.4 Outline of the Thesis

This thesis is structured as follows. Chapter 2 reviews some basic definitions, statistical measures of complex network theory. In particular, we introduce the theory of cointegration, error correction models and unit root tests that have been adopted throughout this work. Further, the statically validation test is employed for the multiple significance tests to construct the ECM-based financial networks.

In Chapter 3, the dynamic analysis in terms of the evolution of short-term correlation, long-term cointegration and ECM-based long-term Granger causality between each pair of US (S&P 500), UK (FTSE 100), and Eurozone (EURO STOXX 50) stock markets over the period of 1980–2015 using the rolling-window technique. In particular, a comparative analysis of pairwise dynamic integration and causality of stock markets, measured in common and domestic currency terms, is conducted to evaluate comprehensively how exchange rate fluctuations affect the time-varying integration among the S&P 500, FTSE 100 and EURO STOXX 50 indices.

Chapter 4 seeks to incorporate the long-run cointegration and short-run error correction mechanisms to construct the financial networks for quantifying the connectedness amongst 46 stock markets worldwide from January 2007 to June 2017. By building up the static global stock market network, the topological structure reflects the regional market integration and segmentation. The dynamic international stock market networks further reveal the time-varying properties of both error correction effect and long-run equilibrium relations amongst 46 stock markets worldwide during periods of financial turmoils and implementation of the QEs by the Fed, BoE, BoJ, and ECB respectively. Especially, the network metrics, namely, average strength and degree, network density, clustering coefficient, reciprocity, and average path length are used to observe the time-varying structure of the dynamic world stock markets. Finally, to provide a better understanding of how financial turmoils as well as the periods that QEs implementation are transmitted across markets, the potential differences and/or similarities in dynamic equilibrium self-adjustment effects of the US, UK, Japanese, and "PIIGS" countries' (i.e., Portugal, Italy, Ireland, Greece and Spain) stock markets are re-investigated.

Chapter 5 is concerned with the financial effects of Brexit-vote on the stocks in the British stock market. Specifically, we construct corresponding stock networks using the ECM models to explore the short-run self-correction mechanism and long-run equilibrium across stocks from sectoral-level before and after the Brexit-vote. Then, in order to extract the most important information from the ECM-based stock networks, the minimal spanning tree (MST) and hierarchical cluster analysis are applied for filtering network and to detect the taxonomy and hierarchical topological structure based our proposed Jaccard distance metric.

Finally, general conclusions and future perspectives of the studies presented in this thesis are exposed in Chapter 6.

Chapter 2

Theoretical Framework

Over the last few years, complex networks have been intensively studied across different domains, especially in Internet technology, biological engineering, social science, and nonlinear science etc. [29]. Generally, a complex network consists of a large number of nodes and linkages, in which nodes represent different individuals in a complex system, and the connections between any two nodes represent their mutual interdependencies. Since complex networks can provide novel insight regarding topology, organization, modular (cluster, community) structure, etc., it has been gradually becoming an important tool to study the interrelationship between different agents in the financial market [29, 30]. In particular, combining the complex networks and econometric measures can shed some light on the connectedness of financial assets and systemic risk issue in the financial market.

2.1 Complex Network Theory

2.1.1 Graph Representation of Complex Networks

A network can be represented by a graph $G(N, E, W)$ in Fig. 2.1, where the set of vertices N represents financial assets and the set of edges E denotes interdependencies between pairwise financial assets. In a network, the direction of the edges is crucial and according to the direction of links, the networks can be divided into the directed and undirected one in Fig. 2.2. Furthermore, since the strength, capacity or intensity of the interdependence between vertices in a network may be heterogeneous, therefore, a weighted network can be created according to the strength of pairwise connections in Fig. 2.3.

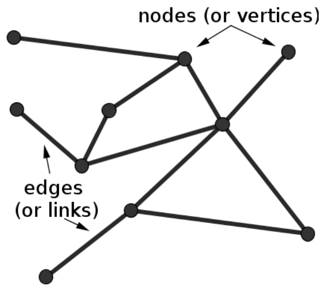
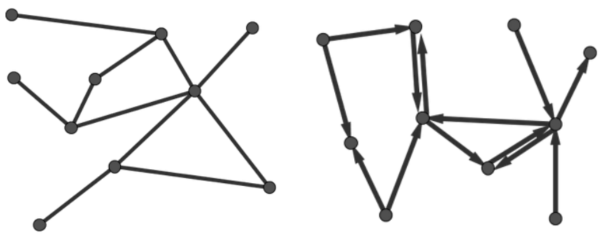


Fig. 2.1. Small example of a network with labeled nodes and edges.



(a) An undirected network (b) A directed network

Fig. 2.2. Small examples of the directed and undirected networks.

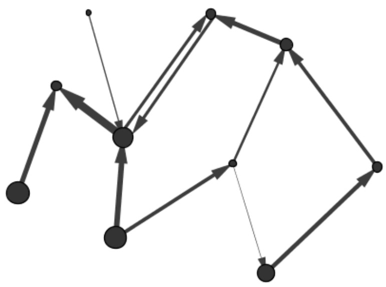


Fig. 2.3. A small example of the directed and weighted network.

To completely describe a network, let A be the $N \times N$ adjacency matrix of a directed network with N vertices:

$$A_{ij} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \tag{2.1}$$

and the element with same weight in the network being:

$$A_{ij} = \begin{cases} 1, & \text{if there is an edge pointing from vertex } j \text{ to vertex } i; \\ 0, & \text{if node } i \text{ and } j \text{ are not connected to each other.} \end{cases} \tag{2.2}$$

In general, the adjacency matrix of an undirected network is symmetric with same weight ($A_{ij} = 1$), namely,

$$A_{ij} = A_{ji}. \tag{2.3}$$

While, for the weighted network, the elements of the adjacency matrix carry the different weight of the edge as

$$A_{ij} = w_{ij}. \tag{2.4}$$

2.1.2 Statistical Characteristics of Complex Networks

Network Degree and Strength

A key property of each vertex in the network is its degree, which measures the number of links connected to a vertex. For the undirected network, a node i's degree is described as

$$k_i = \sum_{j=1}^{N} A_{ji} = \sum_{i=1}^{N} A_{ji}. \tag{2.5}$$

For directed networks, the in- and out-degree of node i can be represented as

$$D_{i \leftarrow \bullet} = \sum_{i=1}^{N} k_i^{in}, \tag{2.6}$$

$$D_{\bullet \leftarrow i} = \sum_{i=1}^{N} k_i^{out}, \tag{2.7}$$

where k_i^{in} is the number of incoming connections or *in-degree*, and k_i^{out} denotes the number of outgoing linkages or *out-degree*.

The strength s_i of node i measures the total weights that pointing from other nodes to i, for the undirected and weighted network:

$$s_i = \sum_{j=1}^{N} w_{ji} = \sum_{i=1}^{N} w_{ji}, \tag{2.8}$$

The in- and out-strength of node i in the directed and weighted networks are described as

$$S_{i \leftarrow \bullet} = \sum_{i=1}^{N} s_i^{in}, \tag{2.9}$$

$$S_{\bullet \leftarrow i} = \sum_{i=1}^{N} s_i^{out}, \tag{2.10}$$

where s_i^{in} is the incoming total weight or *in-strength*, and s_i^{out} is outgoing total weights or *out-strength* of node i, respectively.

Average Network Degree and Strength

The average network degree $< k >$ is an important quantitative network statistics, which quantifies the average number of connection in a network [30]. The average network degree of a directed network is described as

$$< k >= \frac{1}{N}\sum_{i=1}^{N}(k_i^{in} + k_i^{out}) = \frac{L}{N}, \tag{2.11}$$

in which N is the total vertices of the network, L is the actual total number of links in the network. k_i^{in} is the incoming degree of vertex i, which measures the total number linkages that point to vertex i. The outgoing degree of i is presented as k_i^{out} and measures the number of links that point from i to other vertices in the network.

The average network strength $< w >$ of the network is presented as follows

$$< w >= \frac{1}{N}\sum_{i=1}^{N}(s_i^{in} + s_i^{out}) = \frac{W}{N}, \tag{2.12}$$

where N is the number of vertices, W is the total strength of a network. s_i^{in} measures the in-strength of vertex i, which represents the total incoming weights assign to the node i, and s_i^{out} is the out-strength of i and describe the total outgoing weights of node i.

Network Density

The network density D is an indicator of network health and functionality and it is defined as the ratio between the actual connections and all possible connections in a network. Generally, for a directed graph with no loop can have at most $N(N-1)$ possible linkages, therefore the network density of a directed graph is presented as

$$D = \frac{L}{N(N-1)}, \tag{2.13}$$

in which L is the actual number of edges and N is the number of vertices in the network.

Clustering Coefficient

The average clustering coefficient $\bar{C}$ is a measure of the local compactness of a network. The quantity C_i is the local clustering coefficient of node i, expressing how the neighbors of two adjacent nodes have a link in between. For a node i with degree k_i, the C_i is defined as

$$C_i = \frac{2e_i}{k_i(k_i-1)} = \frac{\sum_{jm} a_{ij}a_{jm}a_{mi}}{k_i(k_i-1)}, \tag{2.14}$$

where k_i denotes the number of neighbors of vertex i, e_i is the number of the linkages existing between the neighbors of vertex i. The average clustering coefficient at a specific threshold for the entire network is defined as the average of the local clustering coefficient

C_i over all the nodes in the network and can be described as

$$\bar{C} = \frac{1}{N} \sum_{i=1} C_i, \tag{2.15}$$

Reciprocity

The reciprocity r is a measure of the likelihood of vertices in a directed network to be mutually linked [31]. The reciprocal link of a directed link pointing from i to j is a link pointing from j to i. When two nodes i and j interact as peers, information transfer will in both directions, we take account this to be a symmetric or reciprocated interaction. On the other hand, if a node i transfers information to j, while j will not transfer in return, this is an asymmetric or unreciprocated interaction. The reciprocity r is presented as follows

$$r \equiv \frac{L^{\leftrightarrow}}{L} \equiv \frac{\sum_{i \neq j} a_{ij} a_{ji}}{\sum_{i \neq j} a_{ij}}, \tag{2.16}$$

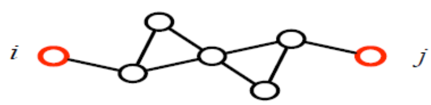
in which the total number of directed links in the network is given by L, the number of reciprocated links is described by $L^{\leftrightarrow}$. In particular, the reciprocity value of real networks has an intermediate value between 0 and 1, when $r = 1$ is for a purely bi-directional network while $r = 0$ for a purely unidirectional one.

Average Path Length

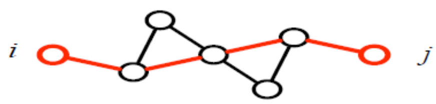
The average path length $< d >$ is the average distance [1] between all pairs of nodes in the network [30]. For a directed network of N nodes, the $< d >$ can be present as:

$$< d >= \frac{1}{N(N-1)} \sum_{i,j \in N, i \neq j} d_{ij}, \tag{2.17}$$

where d_{ij} denotes the length of the path between i and j, and $N(N-1)$ presents all possible connections in a network.



(a)



(b)

Fig. 2.4. Small example of a network path length with $d_{ij} = 4$.

2.2 Cointegration and Error Correction Mechanisms

2.2.1 Cointegration

From an economic point of view, cointegration implies that variables can drift apart in the short-run dynamic, but they will show a long-run equilibrium relationship [14].

[1] In a network, physical distance is replaced by path length.

In other words, if two financial asset prices are cointegrated, it means that the two assets prices share common stochastic trends and move together in the long run [18]. Two common tests employed for testing cointegration are the Engle-Granger [14] and Johansen [32] cointegration tests. Johansen's test is a more powerful test particularly in a multivariate context, while in our study, for the bivariate test, the Engle-Granger cointegration test is applied. Assuming that the two $I(1)$ variables $\left\{X_t, t = 1, ..., n\right\}$ and $\left\{Y_t, t = 1, ..., n\right\}$ are respectively the log-levels of asset price indices, the bivariate cointegration relationship between X_t and Y_t is given by the equation:

$$Y_t = \alpha + \beta X_t + \varepsilon_t, \tag{2.18}$$

$$X_t = \alpha' + \beta' Y_t + \varepsilon'_t, \tag{2.19}$$

where Eq. (2.18) and Eq. (2.19) are called the forward and reverse cointegrating regressions, respectively [14, 33, 34]. Specifically, ε_t and ε'_t denote the mean-zero stationary residuals, i.e., $I(0)$ variable. β (β') is the cointegration coefficient that reflects the effect of independent variables X_t (Y_t) on dependent variable Y_t (X_t) that occurs over future time period [35]. However, in the financial market, even if there is cointegration between X_t and Y_t in the long term, there could be disequilibrium caused by disturbances in the short term. Then the short-run deviation from the long-run equilibrium can be captured by the error correction model (ECM)[14, 15, 36] to guarantee that the two variables do not drift too far apart [37]. It should be aware that before estimating the cointegration and ECM models, we need to test for stationarity of the included variables via unit root tests [14]. Only variables integrated of the same order (i.e. $I(1)$) may be cointegrated, and the unit root tests described in Section 2.2.3 will help us confirm whether our variables are indeed cointegrated.

2.2.2 Error Correction Model

According to the Granger Representation Theorem [14, 15], if Eq. 2.18 hold, a bivariate single-equation ECM model is presented as:

$$\Delta Y_t = \alpha_0 + \delta ECT_{t-1} + \sum_{i=1}^{p} \theta_i \Delta Y_{t-i} + \sum_{i=1}^{q} \gamma_i \Delta X_{t-i} + \eta_t, \tag{2.20}$$

where

$$ECT_{t-1} = \hat{\varepsilon}_{t-1} = Y_{t-1} - [\hat{\alpha} + \hat{\beta} X_{t-1}]. \tag{2.21}$$

The economic intuition arising from this bivariate ECM model in Eq. (2.20) is that the current changes Y_t is a function of the lagged equilibrium correction term ECT_{t-1} (the degree to which two financial asset price indices are outside of their equilibrium in the previous time period $t-1$), lagged changes of Y_t (i.e., $\sum_{i=1}^{p} \theta_i \Delta Y_{t-i}$) and X_t (i.e., $\sum_{i=1}^{q} \gamma_i \Delta X_{t-i}$) [38–40]. Assuming the coefficients of θ_i and γ_i on corresponding terms are statistically significant through F-tests in Eq. 2.20, once X_t has changes (increased or decreased) in the period $t-1$ caused by shocks, then Y_t will response immediately to the lagged change of X_t (i.e., measured by $\sum_i^q \gamma_i \Delta X_{t-i}$). This is consist with standard Granger causality test [8, 15, 41], namely, this bivariate ECM model captures the lead-lag behavior between financial asset prices in the short run. But the statistically significant of the term ECT_{t-1} demonstrates that X_t and Y_t also have a equilibrium relationship in previous period $t-1$, where the increased (or decreased) of X_t disturbs the equilibrium state, causing Y_t deviated from the equilibrium. As a result, Y_t will change to correct and converge back to the long run equilibrium steady state position. However, the change in Y_t may not happen instantaneously in the short-term, occurring over future time periods at a speed rate dictated by the adjustment parameter δ through t-test [35]. Finally, in Eq. (2.20), the term η_t denotes the disturbance terms, assumed to be uncorrelated and have zero mean.

Furthermore, the ECM models can be interpreted as long-run causality which runs interactively through the ECT from X_t to Y_t. In sum, the ECM models allow for testing both short run and long run Granger-causality [38, 39] as well as indicating the direction of causality amongst variables, which provides an interesting alternative to the Granger causality test.

2.2.3 Unit Root Tests

Before we proceed further, we perform unit root tests for each financial asset price to identify whether they are $I(1)$ series [2] [14]. The stationarity is tested after taking the first difference by implementing the most popular Dickey-Fuller (hereafter referred to as DF) [42], augmented Dickey-Fuller (hereafter referred to as ADF) and Phillips-Perron (hereafter referred to as PP) unit root tests [43].

The DF and ADF tests are based on the following regression:

$$\Delta y_t = \beta' D_t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t, \tag{2.22}$$

where δ_i equals zero for the DF tests, y_t is the logarithm of the asset price for time period t, D_t is a vector of deterministic terms (constant, trend etc.), γ is the coefficient presenting the process root, $\sum_{i=1}^{p} \delta_i \Delta y_{t-i}$ are lagged values of y_t, p[3] is the lag order of the auto-regressive process, and ε_t is the error term that should be white noise in our case. The null hypothesis is that the asset price series has a unit root ($H_0 : \gamma = 0$), against the alternative that they do not ($H_0 : \gamma < 0$):

$$\begin{array}{ll} H_0 : & \gamma = 0 \ (y_t \text{ has a unit root}) \Rightarrow y_t \sim I(1) \\ H_1 : & \gamma < 0 \Rightarrow y_t \sim I(0) \end{array} \tag{2.23}$$

[2]Note that the integration of order one is denoted by $I(1)$. A stationary process (denoted by $I(0)$) has the property that the mean, variance and autocorrelation structure do not change over time.

[3]The lag length is decided by $p_{\max} = \left[12\left(\frac{T}{100}\right)^{\frac{1}{4}}\right]$, where T is the sample size of an index series. Then, we set $p = p_{max}$ and perform the ADF test to minimize the Schwarz information criterion [44] (hereafter referred to as SIC).

The corresponding t-statistics is

$$t_{\gamma=0} = \frac{\hat{\gamma}}{SE(\hat{\gamma})}, \tag{2.24}$$

where $SE(\hat{\gamma})$ is the standard error of the OLS estimate $\hat{\gamma}$ in the Eq (2.22).

Different from the DF and ADF tests, the advantage of the PP tests over them is that the PP tests are robust to general forms of heteroskedasticity in the error term u_t. Another advantage is that the user does not have to specify a lag length for the test regression.

$$\Delta y_t = \beta' D_t + \pi y_{t-1} + \varepsilon_t, \tag{2.25}$$

where ε_t is $I(0)$ and may be heteroskedastic. The PP tests correct for any serial correlation and heteroskedasticity in the errors σ_t of the test regression by directly modifying the t-statistics $t_{\pi=0}$. The modified t-statistic, denoted Z_t, is given by

$$Z_t = (\frac{\hat{\sigma}^2}{\hat{\lambda}^2})^{1/2} \cdot t_{\pi=0} - \frac{1}{2}(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}) \cdot (\frac{T \cdot SE(\hat{\pi})}{\hat{\sigma}^2}) \tag{2.26}$$

The terms σ^2 and λ^2 are consistent estimates of the variance parameters, and $\sigma^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E[\varepsilon_t^2]$, $\lambda^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E[T^{-1} S_T^2]$ (where $S_T = \sum_{t=1}^{T} \varepsilon_t$), respectively. The null hypothesis for the PP tests is that:

$$\begin{aligned} H_0: &\quad \pi = 0 \ (y_t \text{ has a unit root}) \Rightarrow y_t \sim I(1) \\ H_1: &\quad \pi < 0 \Rightarrow y_t \sim I(0) \end{aligned} \tag{2.27}$$

Once we have established that all financial time series are $I(1)$ in each time window, the Engle-Granger cointegration tests and ECM models could be implemented.

2.3 Statistical Validation Tests

When we implement the cointegration and ECM models between stock market indices, determining whether an observed result is statistically significant requires multiple comparison tests. However, as the number of hypotheses increases so does the probability of incorrect rejections of false positives. Therefore, a multiple hypothesis test correction needs to be done. The False Discovery Rate (hereafter referred to as FDR) is introduced by Benjamini [45], which describes the proportion of false discoveries among total rejections in multiple comparisons. To control and correct the FDR of a family of hypothesis tests, we utilize the Benjamini and Hochberg (BH) procedure [41, 45].

Let us define the obtain p-values as $P^m = (P_1, ..., P_m)$ and associated null hypotheses $H_0^{(m)} = (H_0^{(1)}, ..., H_0^{(m)})$ for the m hypotheses tests and then sort p-values in ascending order as

$$P_{(0)} = 0 \leq P_{(1)} \leq ... \leq P_{(m)}, \tag{2.28}$$

where let $i = 1, 2, ..., m$ be the indices of the ordered p-value. For a pre-specified FDR α $(0 \leq \alpha \leq 1)$, BH_α procedure rejects $H_0^{(1)}, ..., H_0^{(\hat{k})}$ where

$$\hat{k} = \max\left\{P_{(k)} : P_{(k)} \leq \alpha\frac{k}{m}, 0 \leq k \leq m\right\}. \tag{2.29}$$

Finally, under the independence assumption among the tests, the BH procedure controls the FDR at level:

$$\mathrm{E(FDR)} \leq \alpha\frac{m_0}{m} \leq \alpha, \tag{2.30}$$

in which m_0 is the number of the true null hypotheses.

2.4 Representation of the ECM-based Financial Networks

In ECM models, what we are most interested in is the respective error adjustment coefficient δ in Eq. (2.20). If the estimated δ between pairwise stock markets are significant as expected after the Statistical Validation Test described in Section 2.3, afterward, we build up the corresponding ECM-based financial networks.

Let a graph $G(V, E, W)$ represents the directed and weighted ECM-based financial network, where V is the set of vertices which denotes the various financial assets, E is the edge set to represent the short-run error correction effects and long-run cointegration between each pair of vertices. W is the set of edge weights in which w is the weight of the connected edges between nodes v_i and v_j $(i, j = 1, 2, ..., n)$. Each network edge is assigned weight W, which is the error adjustment coefficients between pairwise financial assets. Specifically, if node i reacts to restore disequilibrium to maintain the long-run equilibrium towards node j, then a directed link is drawn from i to j. The adjacent matrix $\mathbf{W}$ of the financial networks can be represented as follows

$$W_{i\to j} = \begin{cases} w_{ji}, & i \text{ responses to its short run deviations to restore cointegration with } j \\ 0, & \text{otherwise} \end{cases} \tag{2.31}$$

The magnitude of w_{ji}, namely, the error correction coefficients indicate the speed of deviations of node i from long-run equilibrium will feed-back on the change in i in order to force the movement towards the long-run equilibrium with node j. It is worth noting that the significant short-run error adjustment effects between financial assets further confirm the existence of a cointegration relationship between pairwise assets in the financial market.

Chapter 3

A Dynamic Analysis of the US, UK and Eurozone Stock Markets under Different Exchange Rates

This chapter has been published in PLOS ONE [46].

Abstract: In this chapter, we assess the dynamic evolution of short-term correlation, long-term cointegration and Error Correction Model (hereafter referred to as ECM)-based long-term Granger causality between each pair of US, UK, and Eurozone stock markets from 1980 to 2015 using the rolling-window technique. A comparative analysis of pairwise dynamic integration and causality of stock markets, measured in common and domestic currency terms, is conducted to evaluate comprehensively how exchange rate fluctuations affect the time-varying integration among the S&P 500, FTSE 100 and EURO STOXX 50 indices. The results obtained show that the dynamic correlation, cointegration, and ECM-based long-run Granger causality vary significantly over the whole sample period. The degree of dynamic cointegration and correlation between pairs of stock markets rises in periods of high volatility and uncertainty, especially under the influence of economic, financial and political shocks. Meanwhile, we observe weaker and decreasing cointegration and correlation among the three developed stock markets during the recovery periods. Interestingly, the most persistent and significant cointegration among the three developed stock markets exists during 2007–09 global financial crisis. Finally, the exchange rate fluctuations, also influence the dynamic correlation, cointegration and ECM-based long-run Granger casual relations between all pairs of stock indices, with that influence increasing under the local currency terms.

3.1 Introduction

The integration among financial markets worldwide has increased markedly of late, due to the rapid flow of capital in the form of direct and indirect investments, and to the globalization of the financial system. In this new era, many countries appear to be more vulnerable than ever before to (global) shocks, as the magnitude and effects of local and international economic, financial and political shocks can be transferred more rapidly in the financial system [47–49]. Furthermore, not only the frequency but also the severity of crises in the markets has increased significantly. In particular, the 2007–09 global financial crisis considerably influenced the international stock markets, and the subsequent European sovereign debt crisis in early 2010 not only had the significant adverse effect on the European stock markets but also affected those outside of Europe [19, 50]. As a consequence, *integration* and *causality* among those markets have attracted the attention of academia, policy makers and individual investors, as they unveil the complex structure of the global market and, practically, they can influence monetary and fiscal policy coordination and international portfolio diversification [51].

Early research focused mainly on the assets' price correlation based on stationary returns [52, 53], and correlation has been widely applied to study the mutual interdependence of financial asset returns [4, 7, 54–58]. Song et al. [55] studied the dynamic correlations between 57 international stock market indices, and their results reported both fast and slow dynamics. They argued that the fast dynamics of correlations were associated with the internal or external critical events, and economic and financial shocks, while the slow dynamics reflected consolidation and globalization. Buccheri et al. [56] investigated the correlations between all pairs of stocks traded in the US stock market. They also confirmed that the fast correlations between individual stocks were associated with exogenous or endogenous events, and the slow dynamics indicated that a different degree of diversification of investment was possible. However, the linear correlation is an indicator of co-movement of two time series based on synchronous changes. It might therefore miss long-run relationships occurring on a long time scale [59–61].

The recognition of the non-stationarity of asset prices led to the exploration of possible long-run relations among international stock markets using the cointegration framework to avoid spurious relationship between financial asset series [14, 32, 36, 62–64]. Cointegration is a statistical concept, pioneered by Granger and Engle [14, 36, 62]. Generally, two variables are said to be cointegrated when a linear combination of the two is stationary, even though each variable may not be stationary [65]. Empirical studies of the cointegration relationships between some major global stock markets have not provided us with consistent results, since using different data samples, time periods, and data frequencies. For instance, Kanas [66] examined the cointegration relationship between the US and six major European stock markets before and after the 1987 "Black Monday" crash. His results showed no evidence of cointegration among the seven markets. On the other hand, Kasa [67] tested the degree of integration of the US, Japanese, UK, German and Canadian stock markets from 1974 to 1990, and found a single cointegrating vector among the five markets. When Arshanapalli and Doukas [61] studied the dynamic interactions among the US, German, French, UK, and Japanese stock markets, they divided the data sample into two periods, pre- and post-October 1987, to better capture the dynamics of cointegration. Their results showed that, in the later period, the degree of cointegration was significantly greater than in the earlier period. We can also emphasize here that, in this paper, we focus on the dynamic cointegration among the stock market indices, as static cointegration cannot capture the changes in interdependence [48, 68–70]. Moreover, in most of the time-varying cointegration studies, the Johansen test [32, 63, 64] has been applied to examine whether one or more cointegrating vectors exist (generally speaking, for more than three variables), while they have not focused on the pairwise dynamic relationship, which is the main contribution of this paper.

The primary feature of cointegrated variables is that their time paths are affected by the extent of any discrepancies from long-run equilibrium. After all, if the system is to return to the long-run equilibrium, the movements of at least some of the variables must respond to the magnitude of the disequilibrium [14, 71]. The Error Correction Model captures this process of adjustment towards an economic equilibrium, and according to Granger's representation theorem [14, 15], there must be causation in at least one direction among the cointegrated variables in the ECM models. Specifically, the long-term Granger causality is evaluated via the significance of the error correction coefficients in the ECM models [16, 72]. The sign and magnitude of the error correction coefficients indicate respectively, that the direction and speed of adjustment towards the long-run equilibrium path. For example, Wahab and Lashgari [33] employed the cointegration technique and ECM to show how the magnitude of adjustments towards the long-run equilibrium in both index and future prices for the S&P 500 and FTSE 100 is formulated for the period of 1988–1992. Their results indicate that future prices exhibit stronger subsequent responses to disequilibrium in the spot prices. In Arshanapalli and Doukas [61], despite that the cointegration relationships existed between the pairwise stock exchange markets of US and France, US and Germany, US and UK in the post-October 1987 period, the insignificant adjustment coefficients of the error correction terms implies that the equilibrium error cannot be used to predict next period's stock market price changes. Olawale and Taofik [73] showed a statistically significant long-run relationship between macroeconomic variables and the FTSE 100 and S&P 500 stock market indices, their results further indicated that US stock market has a quicker speed of adjustment to its long-run equilibrium than that of UK stock market.

Furthermore, Alexander [18, 74] and Miao [75] argued that cointegration and correlation are somewhat related concepts but that some differences exist. For instance, they found that high correlation of asset returns does not necessarily indicate high cointegration in asset prices and vice versa. Actually, correlation is a short-run measure of co-movement and is liable to instability over time. On the other hand, cointegration measures the long-run co-movements in asset prices, which may occur even during periods when correlation appears to be low. In this paper, the differences and similarities between the correlation, the cointegration and ECM-based long-run Granger causality of international stock markets are studied using a dynamic framework that considers the various economic, financial and political shocks in the economy.

Since the replacement of fixed exchange rates with floating ones in the 1970s, economic and financial crises in the markets have led currencies to fluctuate substantially. In particular, Eun and Shim [60] examined the world's nine developed stock markets' interactions in terms of local currency units to avoid the effect of currency devaluation and appreciation after the occurrence of crises. Alexander and Thillainathan [76] found evidence of cointegration when the stock market indices were expressed in local currency terms. Additionally, Voronkova [77] showed a higher degree of cointegration among stock markets in central Europe, France, Germany, UK and US under the local currencies. Furthermore, the effects of currency devaluation or appreciation after the occurrence of crises (or unexpected events) were no longer present when the stock indices they used in their analyses had been converted to the same currency [17, 78, 79]. Hyde et al. [80] found evidence of asymmetries in conditional volatility for local currency returns, while the asymmetry disappeared among the Asian, US and European stock markets when measured using the US dollar currency (It should be mentioned here that Gilmore et al. [69] commented that, when all indices are expressed in US dollar terms, the results of the study are particularly useful to the US, but also to international investors.). On the contrary, Roll [81] argued that such a transformation did not entirely eliminate the influence of exchange rates (see also [82] and [83]). Thus, changes in exchange rates might affect the short-term co-movement behavior between two international stock markets but it has not yet been fully investigated how the dynamic framework might influence them. Hence, in the present paper, we intend to fill this gap and answer the following four fundamental questions:

- How does the pairwise dynamic long-run cointegration changed between international stock indices?
- How does the long-run ECM-based Granger causality varied over time between cointegrated stock indices?
- What are the differences and similarities between the dynamic correlation, cointegration, and long-run ECM-based Granger causality?
- How do the different exchange rates affect both dynamic correlation, cointegration, and long-run ECM-based Granger causality?

With these concerns in mind, the objective of this work is to study the impact of economic, financial, and political episodes on the S&P 500, FTSE 100 and EURO STOXX 50 stock market indices, using the correlation, cointegration and ECM-based long-run Granger causality tests in a dynamic framework. Additionally, we study whether changes in the foreign exchange rates affect the pairwise integration and causality behavior of the stock markets. Overall, the main contributions of this study are as follows. Firstly, we employ a rolling-window technique by choosing a window size of one year for the correlation and cointegration tests for the S&P 500, FTSE 100 and EURO STOXX 50 (EURO STOXX 50 was launched on February 26th, 1998) indices from January 1st, 1980 to December 29th, 2015. In particular, the rolling-window analysis gives us the opportunity to compare the levels of correlation and cointegration relations before and after specific episodes of financial distress over that period. Second, the rolling-window dynamic ECM-based long-run Granger causality tests provide more interesting results not only for the interaction detection but also for the directed causal relations over time. Third, during the periods of economic, financial and political shocks, the difference and similarity of dynamic correlation, cointegration and ECM-based long-run Granger causality between the pairs of stock market indices are detected. Finally, unlike previous studies in the corresponding literature, in this study, the dynamic correlation, cointegration, and ECM-based long-run Granger causality are measured using common and domestic currency terms. Thus, we are able to investigate how the fluctuation of exchange rates influences the *integration* and *causality* behavior between all the combinations of pairs from those three stock market indices from 1980 to 2015.

The remainder of this chapter is structured as follows. Subsection 3.2 provides the data and preliminary analysis. Subsequently from Subsection 3.3–3.8 present empirical results. Finally, Subsection 3.9 states our conclusions.

3.2 Data Description

We choose three international stock market indices in this study, to cover the three major, most liquid and developed financial markets in the world, i.e., US, UK and Eurozone. The data consist of two groups: three stock indices, the S&P 500, FTSE 100 and EURO STOXX 50, and three exchange rates, the USD (US dollar), GBP (UK pound) and EUR (Euro). All data are from Thomson Reuters DataStream.

In order to avoid the "non-synchronous trading effect" [60, 84], which is related to the fact that not all the markets are open during the same hours of the day, we use weekly data. The data range from January 1st, 1980 to December 29th, 2015, apart from that for the EURO STOXX 50 index, for which data was available from February 26th, 1998. The samples of the S&P 500 and FTSE 100 consist of 1879 observations each, and that of the EURO STOXX 50 index contains 932 observations. Fig. 3.1 depicts the original stock price index and returns for the S&P 500, FTSE 100 and EURO STOXX 50, respectively. Over the past 35 years from 1980 to 2015, the price indices of the S&P 500 and FTSE 100 appear to have stochastic trends and seem to reveal similar behavior from the beginning until 2009. Two peaks occurred, in 2000 and 2007, followed by sharp declines in 2001 and 2008 for all three indices. Then, the S&P 500 recovered strongly from 2009 until the end of December 29th, 2015, while the performance of the FTSE

100 and EURO STOXX 50 indices lagged behind that of the S&P 500 but exhibited similar increasing trends. Furthermore, from the movement of the returns in Fig. 3.1, we can deduce that the downward movements of the S&P 500, FTSE 100 and EURO STOXX 50 tend to be associated with large returns. Table A.1 provides the name and date of each economic and financial shock that occurred around the world between 1980 and 2015. In addition, to study how the exchange rates fluctuations affect the pairwise interdependence of stock markets, the pairs of stock price indices, namely, S&P 500 with FTSE 100, S&P 500 with EURO STOXX 50, and FTSE 100 with EURO STOXX 50, each of those pairs are converted using the same currency (i.e., fixing the exchange rates fluctuations) and their domestic currencies (i.e., permitting exchange rates fluctuations). The details of our sample are reported in Table 3.1.

Since our indices have different scales, they must be rescaled so as to be comparable. Thus, the first step is to calculate the percentage changes of each stock index series, which are given by

$$\Delta_i(t) = \frac{P_i(t)}{P_i(t-1)}, \text{ for all t} \geq 2, \tag{3.1}$$

where $P_i(t)$ is the price of index i in week t. For the rescaled index series $R_i(t)$, we set the first entry in each series to be $R_i(1) = 1$, and then $R_i(t)$ is expressed, for all subsequent entries in each series, by

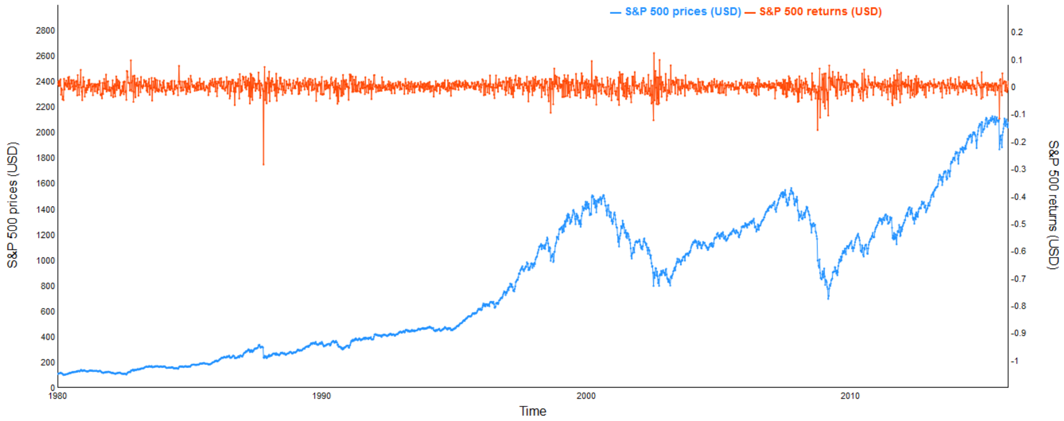
$$R_i(t) = R_i(t-1) * \Delta_i(t), \text{ for all t} \geq 2. \tag{3.2}$$

After rescaling the original stock index series, we finally transform them into natural logarithms [1] for the cointegration and error-correction mechanism test.

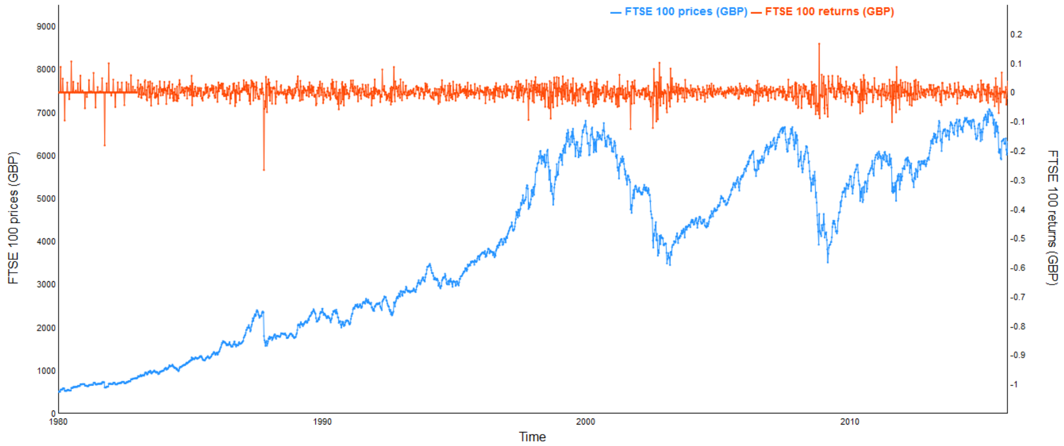
Table 3.1. The three pairs of indices out of S&P 500, FTSE 100 and EURO STOXX 50, and the different currency terms used.

Stock Market Indices	**Common Currency**	**Common Currency**	**Domestic Currencies**
S&P 500 vs. FTSE 100	USD/USD	GBP/GBP	USD/GBP (GBP/USD)
S&P 500 vs. EURO STOXX 50	USD/USD	EUR/EUR	USD/EUR (EUR/USD)
FTSE 100 vs. EURO STOXX 50	GBP/GBP	EUR/EUR	GBP/EUR (EUR/GBP)

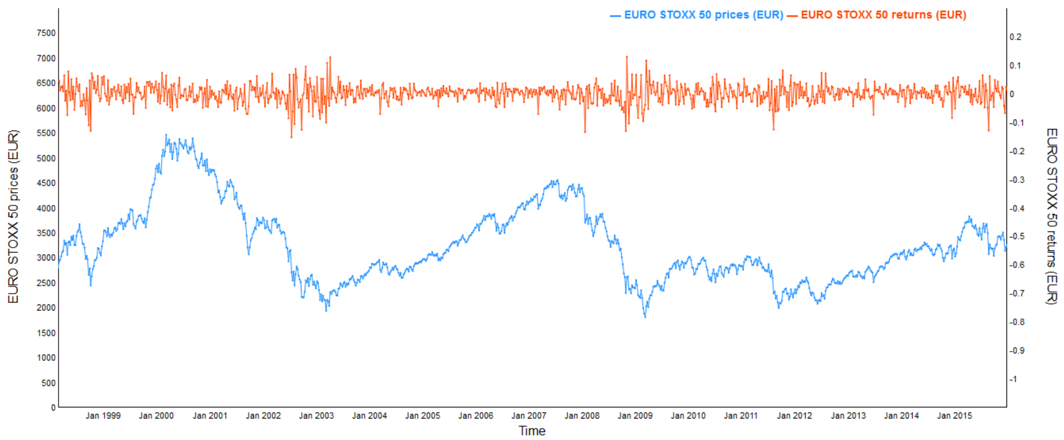
[1] The study has used natural logarithm for the transformation of weekly data as well as to minimize the heteroscedasticity in the value of the level series.



(a) Weekly stock price indices and returns of S&P 500 from 1980–2015



(b) Weekly stock price indices and returns of FTSE 100 prices and returns from 1980–2015



(c) Weekly stock price indices and returns of EURO STOXX 50 prices and returns from 1998–2015

Fig. 3.1. Time variations in weekly stock price indices and returns of S&P 500, FTSE 100 and EURO STOXX 50 based on local currency terms.

3.3 Rolling Window Technique

To measure the time-varying pairwise correlation, cointegration and ECM-based long-run Granger causality of the stock markets, a rolling window size of $l = 48$ (i.e., 48 weeks per calendar year) is chosen as the frame in the study [85]. Specifically, we first choose a rolling window of size l, which is the number of observations per rolling window, and we set the number of increments between successive rolling windows. Then, the entire sample T is converted into $N = T - l + 1$ sub-samples. Thus, the first rolling window contains observations for the first period through l, the second rolling window contains observations for the second period through $l + 1$, and so on.

3.4 Short-run Correlation Analysis

In our study, the first measure of the extent of the financial markets' integration is provided by the correlations estimated using dynamic Pearson correlation analysis. For the correlated variables, the standard method of Pearson correlation is used [86]. The analysis is based on the weekly logarithmic return after rescaling, which is given by Eq. (3.3) for each stock index i:

$$r_i(t) = \ln R_i(t) - \ln R_i(t-1), \tag{3.3}$$

where $R_i(t)$ is the price of index i in week t after rescaled by Eq. (3.1) and (3.2). Then, in each time window, the Pearson correlation coefficient between returns i and j is given by

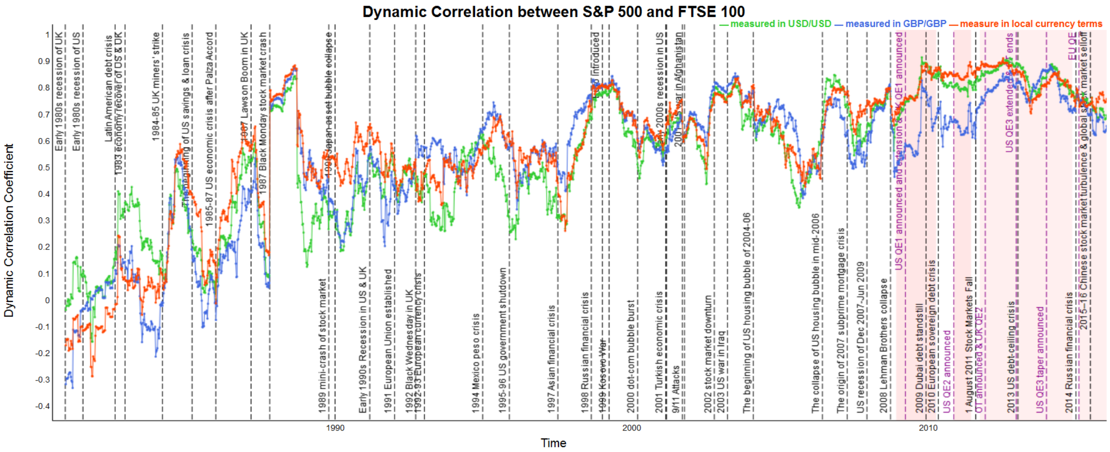
$$C_{i,j} = \frac{\langle [r_i(t) - \mu_i][r_j(t) - \mu_j] \rangle}{\sigma_i \sigma_j}, \tag{3.4}$$

where μ_i and μ_j are the sample means and σ_i and σ_j are the standard deviations of the two returns i and j.

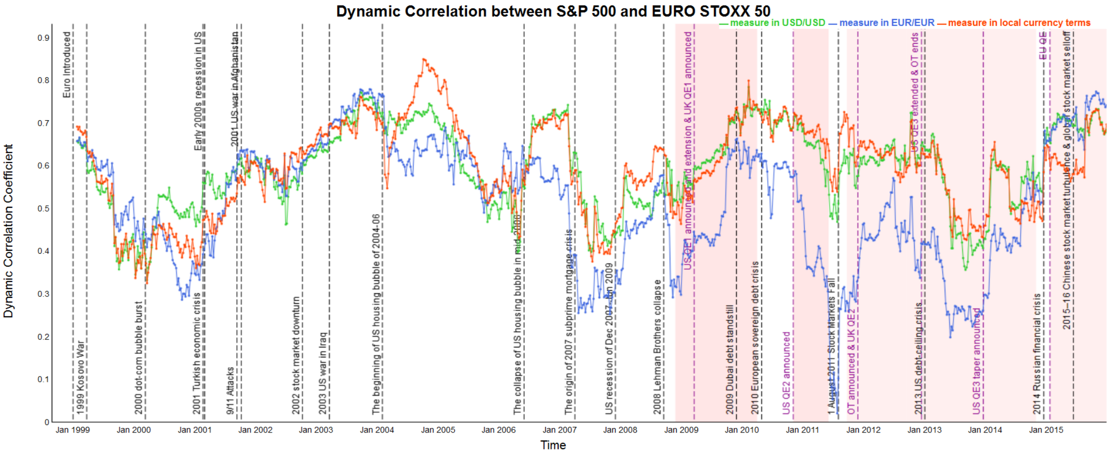
Fig. 3.2(a)–3.2(c) illustrate the dynamic correlation coefficients for each pair of stock market indices from the S&P 500, FTSE 100 and EURO STOXX 50, when measured in the same and local currency terms from 1980 to 2015. A statistical summary is provided in the form of strongest, weakest and average absolute value of correlation coefficients in Table 3.2.

Table 3.2. Statistical Analysis of Dynamic Correlation Coefficients.

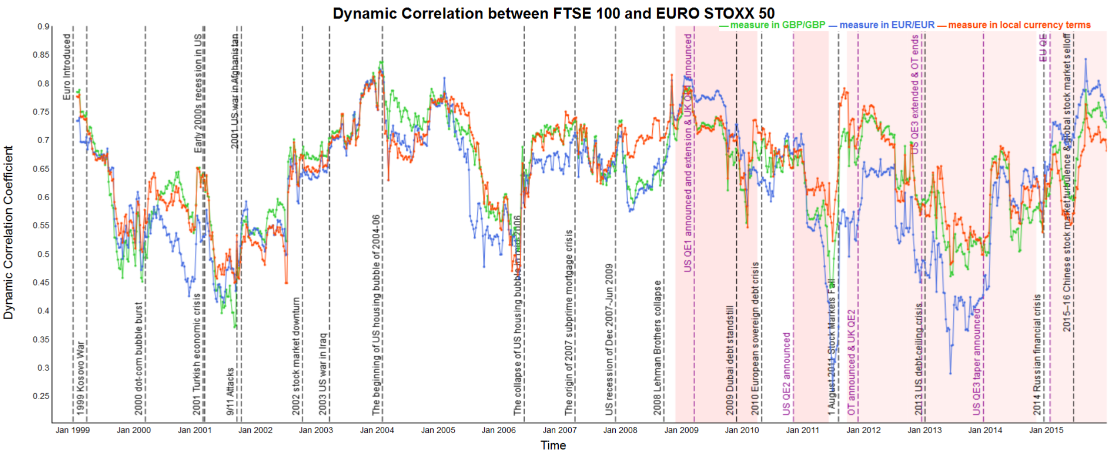
Stock Market Indices	**Strongest Coeff**	**Weakest Coeff**	**Average Coeff**
S&P 500 vs. FTSE 100			
Measured in USD/USD	0.917	0.0014	0.544
Measured in GBP/GBP	0.888	0.0003	0.545
Measured in local currencies	0.914	0.0020	0.586
S&P 500 vs. EURO STOXX 50			
Measured in USD/USD	0.786	0.3340	0.596
Measured in EUR/EUR	0.781	0.0215	0.515
Measured in local currencies	0.851	0.3260	0.597
FTSE 100 vs. EURO STOXX 50			
Measured in GBP/GBP	0.838	0.3730	0.646
Measured in EUR/EUR	0.843	0.2620	0.621
Measured in local currencies	0.822	0.4500	0.652



(a) Dynamic correlation between S&P 500 and FTSE 100 over 1980–2015



(b) Dynamic correlation between index S&P 500 and EURO STOXX 50 over 1998–2015



(c) Dynamic correlation between FTSE 100 and EURO STOXX 50 over 1998–2015

Fig. 3.2. Dynamic correlation between S&P 500, FTSE 100 and EURO STOXX 50 based on common and local currency terms over 1980–2015. The red shading represents implementation of QE policies.

Observing Fig. 3.2(a)–3.2(c), the dynamic correlation coefficients between all pairs of stock market indices tend to rise significantly with the economic, financial and political shocks under the influence of high market volatility and uncertainty in the system. However, gradually decreasing during the periods of recovery of the stock market after the shocks. Fig. 3.2 also reflects that the dynamic integration between the US and UK stock markets has a consistently positive trend over 1980–2015, compared with the relatively stable and higher-valued trend between the US and Eurozone, UK and Eurozone. Furthermore, in Table 3.2, we report that the average correlation coefficient between the S&P 500 and FTSE 100 is 0.544 in USD/USD, 0.545 in GBP/GBP, and 0.586 in local currencies. That between the S&P 500 and EURO STOXX 50 is 0.596 in USD/USD, 0.515 in EUR/EUR, and 0.597 in local currency terms, and that between the FTSE 100 and EURO STOXX 50 is 0.646 in GBP/GBP, 0.621 in EUR/EUR, and 0.652 in local currency units. These results suggest that, when measured in local currency terms, the correlation is stronger. In addition, Fig. 3.2 and Table 3.2 provide evidence that the FTSE 100 and EURO STOXX 50 have the strongest correlation compared with the S&P 500 and FTSE 100 or the S&P 500 and EURO STOXX 50. Besides, the strongest correlation between the S&P 500 and FTSE 100 occurs during period 9, namely, the 1987 "Black Monday" stock market crash. However, the strongest coefficients between the S&P 500 and EURO STOXX 50, and between the FTSE 100 and EURO STOXX 50, both occur during period 31, i.e., at the beginning of 2004–06 US housing asset bubble period. In particular, when we take into account how the changes of exchange rates influence the dynamic correlation coefficients between all three stock market indices, the weakest correlation between the S&P 500 and FTSE 100 is measured in GBP/GBP during periods 4, and 35–49, all of which saw the USD depreciated against the GBP. For the S&P 500 and EURO STOXX 50, we observe the weakest correlation during periods 31–49 when using EUR/EUR, which associated with the USD's devaluation against the EUR. Furthermore, in periods 42–49, the correlation between the FTSE 100 and EURO STOXX 50 becomes weaker when expressed in EUR/EUR, and again the GBP depreciated against the EUR during that period.

The linear correlation analysis is performed to ascertain the degree of co-movement among the three developed stock markets based on stationary returns. However, such analysis might miss long-run relationships occurring on a long time scale and lack the information of the direction of interaction between international stock markets. For the non-stationary financial asset price series, the implementation of the dynamic cointegration and ECM tests could be used to verify whether a long-term relationship exists, and to examine the long-run Granger causality, respectively.

3.5 Results of Unit Root Tests

Before estimating the dynamic cointegration in the long-run, we firstly employ the ADF and PP unit root tests models to examine the integration order of the S&P 500, FTSE 100 and EURO STOXX 50 indices in log levels and first differences. In Figs. A.1–A.3, we plot the dynamic p-values of ADF and PP t-statistic of the S&P 500, FTSE 100 and EURO STOXX 50 indices (expressed in USD, GBP and EUR, respectively) in logarithm levels. We observe that the p-values are above the red lines (5% significance level) for the vast majority of time windows. Thus, the null hypothesis of $\gamma = 0$ is accepted, and the stock indices are found to be non-stationary in log levels. However, for those cases in which the p-values are below the red lines, we have to delete the corresponding rolling windows to ensure that all stock index series under all sub-sample windows are $I(1)$, i.e., non-stationary in logarithm levels and stationary in first differences. Since results imply that the stock index series contain a unit root in log levels and thus should be differenced to achieve stationarity. For the sake of space, we have not included the figures here. However, the dynamic p-values of ADF and PP t-statistic of the S&P 500, FTSE 100 and EURO STOXX 50 indices (expressed in USD, GBP and EUR, respectively) in first differences are all below the 5% significance level. The results of the rolling-window ADF and PP tests suggest that the S&P 500, FTSE 100 and EURO STOXX 50 indices are $I(1)$ processes, and then we can implement the cointegration tests to examine whether there are long-run cointegration relations between the pairs of processes.

3.6 Dynamic Long-run Cointegration Analysis

Pairwise dynamic cointegration of stock indices is indicated by the p-values of the DF and PP unit root tests of the residual series; see Figs. 3.3–3.8 which show the p-values after BH-FDR control for both $I(1)$ process. In the multiple statistical tests, an FDR p-value that is consistently less than 0.05 or 0.01 would suggest that the null hypothesis of no cointegration could be rejected. Practically, this would mean that there is a long-run cointegration relationship between that pair of stock indices. Generally, the smaller the obtained p-values, the null hypothesis that there is no cointegration relationship can be rejected at lower values of the chosen statistical threshold. The one-year rolling cointegration estimation and the results based on DF and PP tests models for the dynamic p-values over the period 1980–2015 are plotted in Figs. 3.3 and 3.4 for the S&P 500 and FTSE 100 measured in USD/USD, GBP/GBP, and their domestic currency units. Figs. 3.5 and 3.6 display the S&P 500 and EURO STOXX 50 measured in USD/USD, EUR/EUR and their local currency units, and Figs. 3.7 and 3.8 depict the FTSE 100 and EURO STOXX 50 measured in GBP/GBP, EUR/EUR and their local currency units. Over 1980–2015, we can observe that the dynamic p-values vary over time, indicating significant fluctuation in the degree of integration among the different indices and currencies.

Table 3.3. Observed periods of cointegration and Granger causality (in long run) between the S&P 500 and FTSE 100 during 1980–2015.

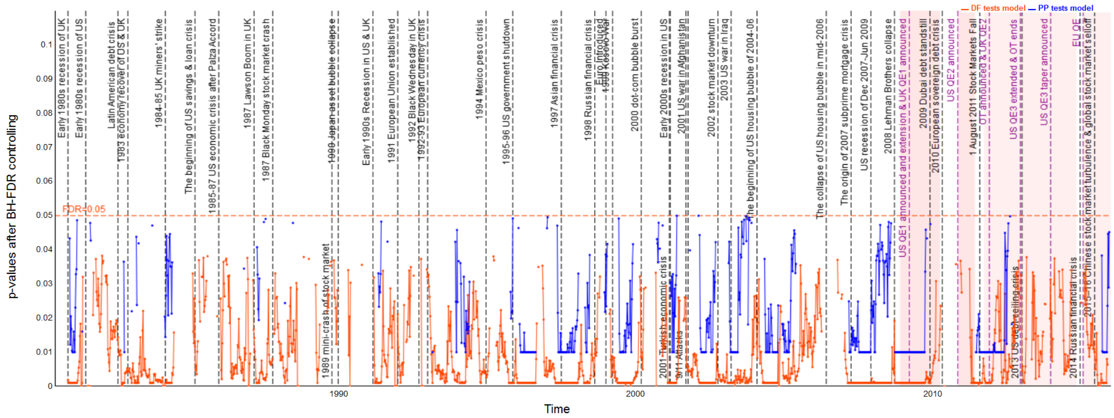
S&P 500 vs. FTSE 100	**Observed periods**		
S&P 500 → FTSE 100	USD/USD	GBP/GBP	GBP/USD
At 1% significance level	periods 1, 3–5, 8–10	periods 1, 3, 4, 9	periods 1, 3–5, 8, 9
	periods 13, 14, 16, 18–20	periods 13–14,16, 18–20	periods 13, 16, 18–20
	periods 23, 25–31, 33–38	periods 23, 25–30, 33–38	periods 23, 25–31, 33–44
	periods 41–44, 49, 52–53	periods 42–44, 49–50, 52–53	periods 46–48, 52–53
At 5% significance level	periods 2, 6, 7	periods 2, 6–8, 10–12	periods 2, 6, 7, 10–12
	periods 11, 17, 24, 32	periods 17, 24, 31, 32	periods 14, 17, 24, 32
	periods 39, 40, 46–48, 50, 51	periods 39, 40, 45–48, 51	periods 45, 50–51
S&P 500 causes FTSE 100	periods 1–10, 13–14, 18, 22–23	periods 1–2, 7, 9, 12–14, 16–17	periods 1–2, 9, 12–14, 17
	periods 27–29, 31, 33–34	periods 22–24, 26–27, 29, 31–34	periods 19–24, 26, 31–38
	periods 42, 46–49, 52–53	periods 38, 41, 44, 46–51	periods 45–51
(53 sub-periods)	53%	53%	55%
FTSE 100 → S&P 500	USD/USD	GBP/GBP	USD/GBP
At 1% significance level	periods 1, 4, 5, 8	periods 1, 4, 7–9	periods 1, 4, 5, 8, 9
	periods 16–21, 23, 25–31	periods 13, 16, 18–20, 23	periods 13, 15, 16, 18–21, 23
	periods 33–38, 41–44	periods 25–30, 33–38	periods 25–30, 32–40, 42, 44
	periods 49–53	periods 41–44, 49, 52–53	periods 49, 52–53
At 5% significance level	periods 2, 3, 6, 7, 9, 11, 13–15	periods 2, 5, 6, 11, 14, 31	periods 3, 7, 11, 12, 14, 24
	periods 24, 32, 39–40, 45–48	periods 39, 46–48	periods 31, 41, 50–51
FTSE 100 causes S&P 500	periods 1–2, 5, 7, 9, 11	periods 1, 3–5, 7–8, 11, 13	periods 1, 3–5, 11, 15–16
	periods 15–17, 19–21, 24–25	periods 15–16, 18–19, 21, 24, 26	periods 18, 24, 27–31, 40
	periods 30–31, 35, 40, 50–53	periods 28, 30–31, 35–38	periods 42, 52–53
(53 sub-periods)	42%	42%	34%

Note that, to indicate that A cointegrates with B, we write $B \to A$.

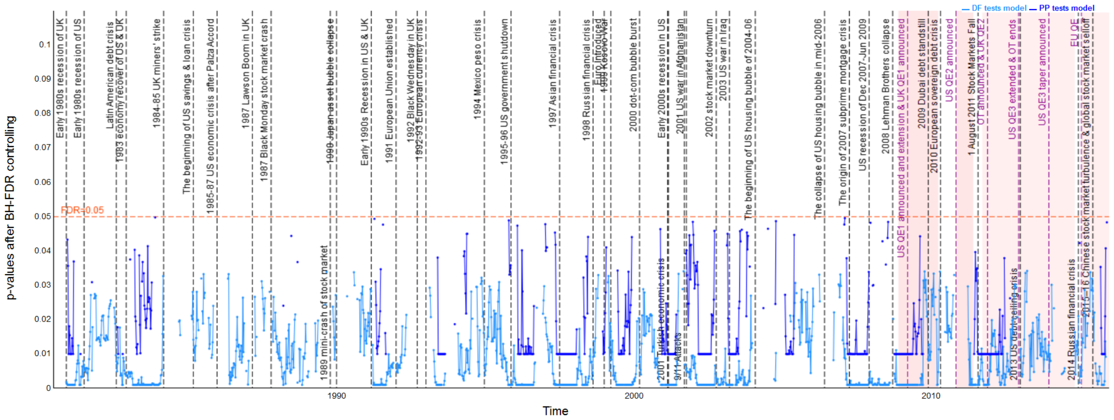
3.6.1 Cointegration between S&P 500 and FTSE 100 Indices

The dynamic p-values that reflect the extent to which the FTSE 100 cointegrates with the S&P 500, measured in USD/USD, GBP/GBP and GBP/USD, are shown in Fig. 3.3. Table 3.3 summarizes the observed time periods in which the FTSE 100 cointegrates with the S&P 500 at both the 1% and 5% significance levels based on both DF and PP tests of residuals. Combining the results of Fig. 3.3 and Table 3.3, we find that the FTSE 100 cointegrates with the S&P 500 at the 1% significance level during the periods associated with the economic, financial and political shocks, from 1980 to 2015 based on both DF and PP tests. However, the results based on PP tests model are non-significant from 1980 to 1993. Based on the degree of persistent cointegration, an interesting finding is that when compared to the shocks that occurred in the developing countries (e.g., see periods 17, 19, 21), the shocks in the US market (e.g., see periods 18, 27, 29, 33–35) have a more significant influence on the FTSE 100's cointegration behavior with the S&P 500. In particular, the most persistent periods of the FTSE 100's cointegration with the S&P 500 are periods 33–35 based on both DF and PP tests, namely, the recent 2007–09 international financial crisis, which indicates that the US stock market significantly influenced the UK market during that time. On the other hand, the dynamic p-values exhibit lasting fluctuation during periods 2, 7, 31, 32, and 46–48, at the 5% statistical significance level. The observed results suggest that the

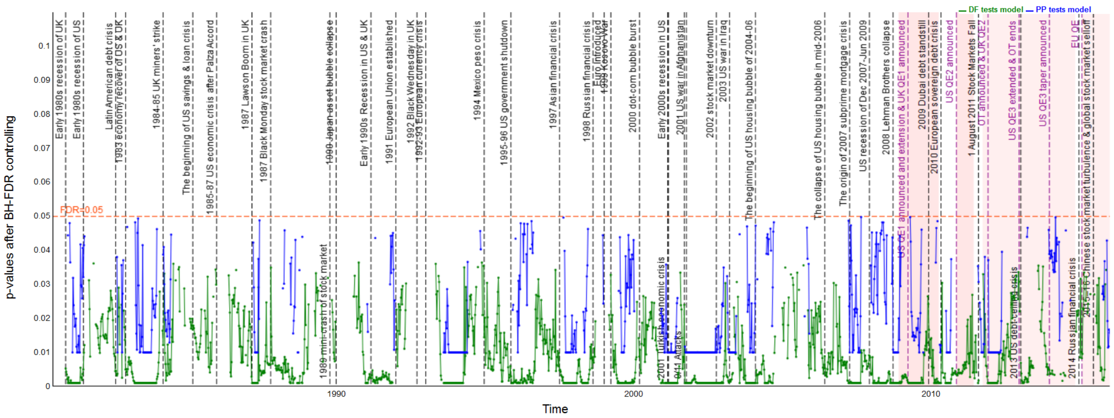
1985–87 US economic crisis caused by the Plaza Accord [87], the continuous impact of the US housing asset bubble in 2004–06, and the US QE3 announced and taper policies implemented by the Federal Reserve that are the most significant causes of the evidence of the FTSE 100's cointegration with the S&P 500 [20]. Fig. 3.3(a)–3.3(c) also illustrates the comparative analysis of how exchange rate movements affect the cointegration of the FTSE 100 with the S&P 500 based on both DF and PP tests. At first sight, the difference between the cointegration as measured in the same currencies versus local currencies seems relatively small, while in periods 9, 39–40 and 49 we can observe stronger integration when measured in local currency terms, GBP/USD, which is in line with the findings of Voronkova's study [77]. During period 24, the evidence that the FTSE 100 cointegrates with the S&P 500 can only be found when measured using local currencies, which is consistent with Alexander [76]. Furthermore, there is a stronger possibility that the FTSE 100 cointegrates with the S&P 500 when we measure it using USD/USD and domestic currency terms during periods 5, 16 and 31. On the contrary, the evidence of cointegration disappears when we measure it using GBP/GBP (note that the GBP depreciated against the USD during these periods). Reverse findings are identified during periods 8 and 40. In these periods, the evidence of the FTSE 100's cointegration with the S&P 500 vanishes when measured in USD/USD (the USD depreciated against the GBP during these periods).



(a) FTSE 100's cointegration with S&P 500 measured in USD



(b) FTSE 100's cointegration with S&P 500 measured in GBP

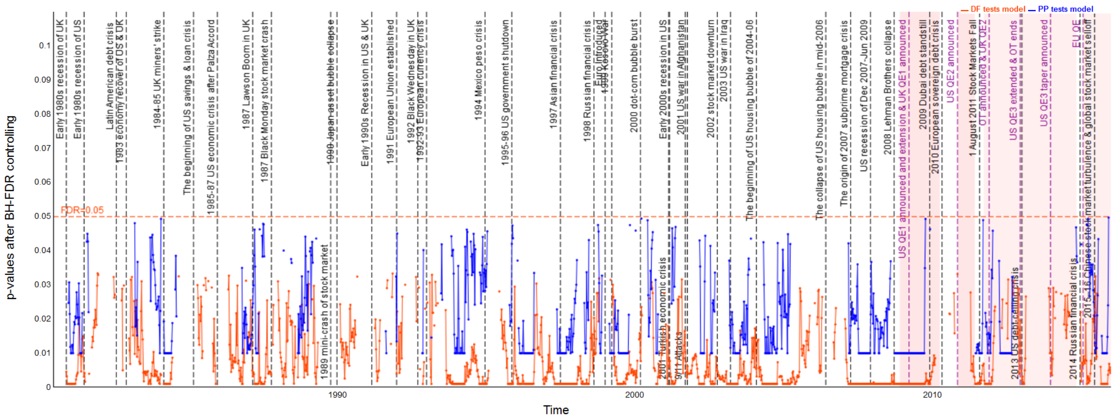


(c) FTSE 100's cointegration with S&P 500 measured in local currencies

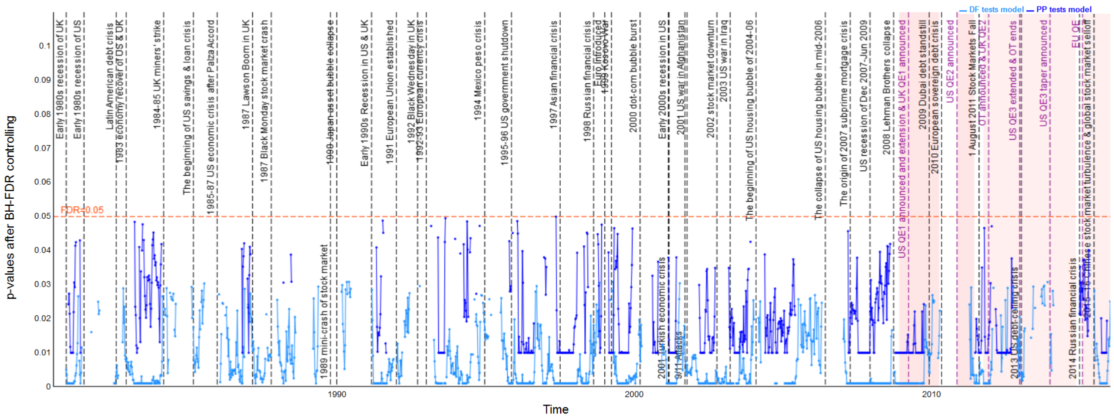
Fig. 3.3. Dynamic p-values (based on DF and PP tests models) after BH FDR controlling showing FTSE 100's cointegration with S&P 500 in USD, GBP and local currency terms, during 1980–2015. The red horizontal line denotes the false discovery rate with 0.05 for the multiple tests; black vertical lines correspond to economic, financial and political shocks during 1980–2015; red shading represents implementation of QE policies.

Fig. 3.4 depicts the dynamic p-values that indicate the S&P 500s cointegration with the FTSE 100, measured in USD/USD, GBP/GBP, and USD/GBP, at both 1% and 5% significance levels based on both DF and PP tests models of residuals. Similarly, Table 3.3 reports the observed times at which the S&P 500 cointegrates with the FTSE 100, all of which are associated with economic, financial and political episodes that occurred during 1980–2015. The most long-lasting period of cointegration occurs during periods 33–35, i.e., during 2007–09 global financial crisis, which was also the case for the FTSE 100's cointegration with the S&P 500. However, when comparing Figs. 3.3 and 3.4, one difference we can see is that the dynamic p-values are greater for the S&P 500 cointegrating with the FTSE 100 than vice versa, which suggests a lower degree of cointegration. In particular, during period 2, the time of the early-1980s recession in the US market, the evidence of the S&P 500 cointegrating with the FTSE 100 disappears. Furthermore, during periods 46–48, when the US QE3 and tapering policies announced, we find evidence that the S&P 500s long-lasting cointegration with the FTSE 100 is weak and almost disappears. Additionally, the evidence indicates that, since the growth of the FTSE 100 lagged significantly behind that of the S&P 500, following the severe shocks caused by 2007–09 global financial crisis and 2010 European sovereign debt crisis, the influence of the UK on the US market was weaker than the reverse. In contrast, the degree of the S&P 500's cointegration with the FTSE 100 tends to be higher than that of the FTSE 100's cointegration with the S&P 500 during period 17, namely, the 1994 Mexican debt crisis. Moreover, we notice that the S&P 500 cointegrating with the FTSE 100 significantly during period 15 (i.e., 1992's "Black Wednesday" in the UK), while the FTSE 100 does not cointegrate with the S&P 500 during that period (see Fig. 3.3). These results imply that the UK currency crisis on September 16th, 1992 not only affected the UK stock market greatly but also enhanced the latter's influence on the US market.

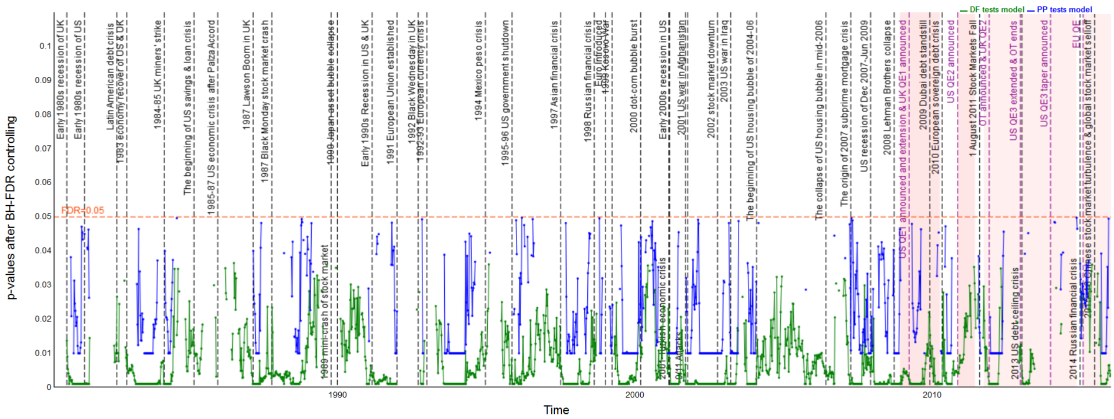
Finally, taking into account the influence of exchange rate movements on the S&P 500's dynamic long-lasting cointegration with the FTSE 100 based on both DF and PP tests results (see Fig. 3.4(a)–3.4(c)), we observe that, during periods 5, 9, 31 and 39, the S&P 500 cointegrates more intensely with the FTSE 100 when they are measured in USD/USD and local currency terms, respectively. In particular, the S&P 500's cointegration with the FTSE 100 can only be identified when using the local currencies during period 40, namely during the 2010 European sovereign debt crisis. Furthermore, our results reveal that, during periods 15, 50–51, the evidence that the S&P 500 cointegrates with the FTSE 100 disappears when measured in GBP/GBP (note that there was depreciation of the GBP against the USD during these periods), while it is stronger when measured in USD/USD and local currency terms. The opposite results are observed during period 13, when a higher degree of cointegration is reported under GBP/GBP and the local currencies, yet there is no evidence of cointegration under USD/USD (note the depreciation of the USD against the GBP at this time).



(a) S&P 500's cointegration with FTSE 100 measured in USD



(b) S&P 500's cointegration with FTSE 100 measured in GBP



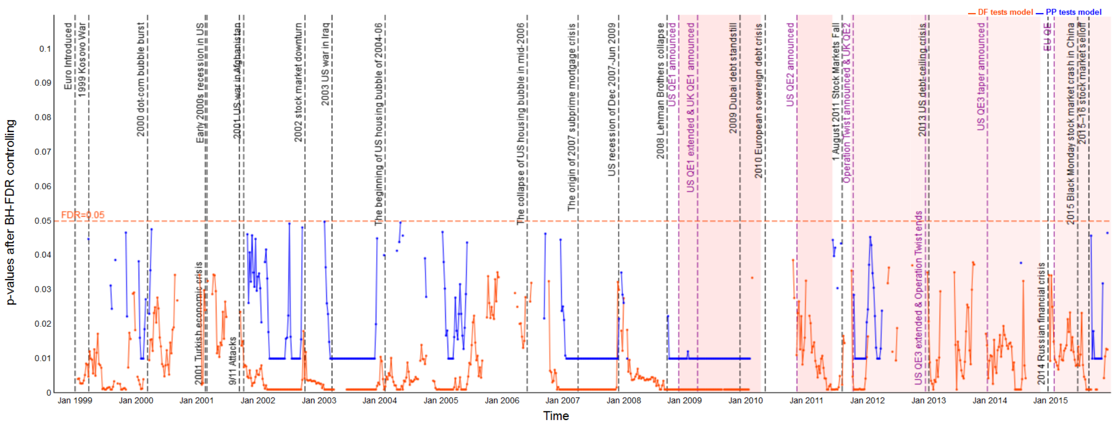
(c) S&P 500's cointegration with FTSE 100 measured in local currencies

Fig. 3.4. Dynamic p-values (based on DF and PP tests models) after BH FDR controlling showing S&P 500 100's cointegration with FTSE 100 in USD, GBP and local currency terms, during 1980–2015. The red horizontal line denotes the false discovery rate with 0.05 for the multiple tests; black vertical lines correspond to external and internal economic, financial and political shocks during 1980–2015; red shading represents implementation of QE policies.

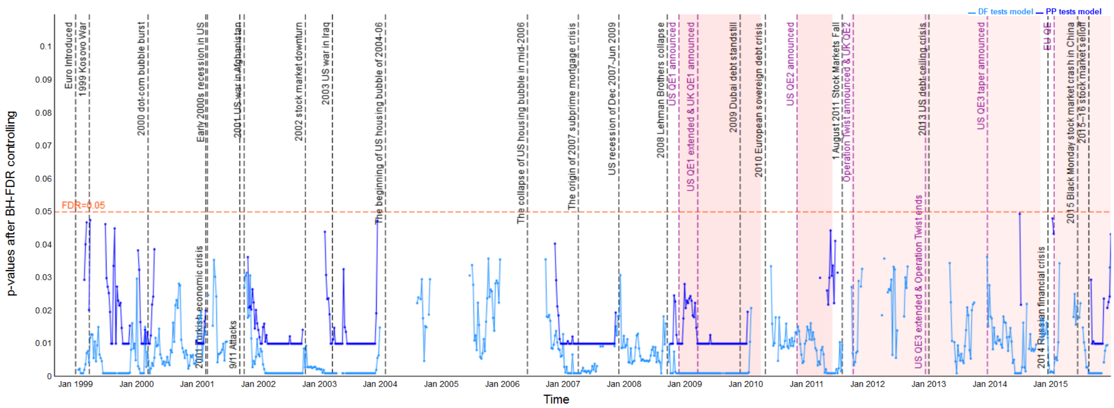
3.6.2 Dynamic Cointegration between the S&P 500 and EURO STOXX 50 Indices

The dynamic p-values based on DF and PP tests of residuals indicating the extent to which the EURO STOXX 50 cointegrates with the S&P 500 and the S&P 500 cointegrates with EURO STOXX 5 under common and local currency terms, are only presented from 1998 to 2015 (see Figs. 3.5 and 3.6). Table 3.4 gives the observed periods of cointegration between stock markets of the US and Eurozone for both the 1% and 5% statistical significance levels. From Figs. 3.5 and 3.6, we can observe similar degrees of long-lasting cointegration of the EURO STOXX 50 with the S&P 500 and vice versa, associated with economic and financial shocks, and once again the cointegration between the S&P 500 and EURO STOXX 50 is most persistent and highest during 2007–09 global financial crisis, out of the whole sample period. However, a significant distinction is that, during periods 24 and 31, namely after the 2000 bursting of the dot-com bubble and during 2004–06 US housing asset bubble, there is stronger cointegration of the S&P 500 with the EURO STOXX 50 than vice versa. However, the opposite is true for periods 46–48, i.e., when the US QE3 and tapering policies were implemented.

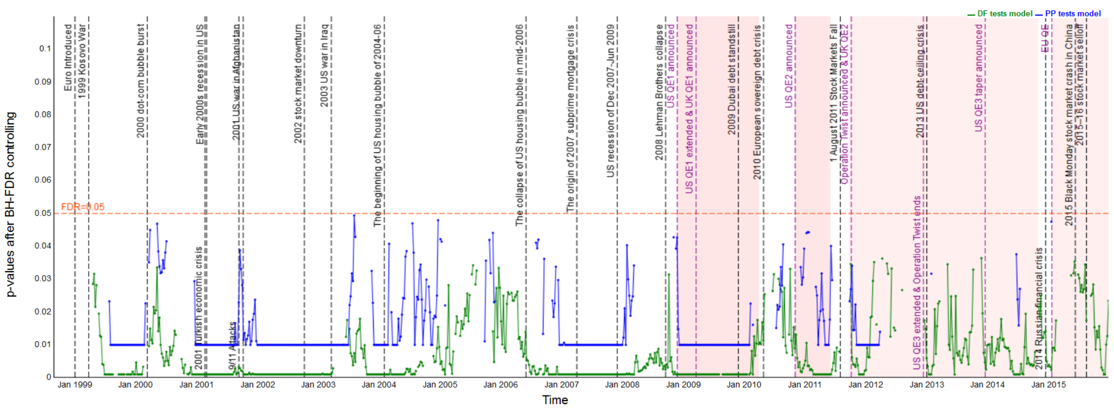
Now turning our attention to how changes in exchange rates influence the integration behavior between the S&P 500 and EURO STOXX 50, we compare Fig. 3.5(a)–3.5(c) and Fig. 3.6(a)–3.6(c). Based on the results of both DF and PP tests models, there is a stronger probability of the existence of cointegration between the S&P 500 and EURO STOXX 50 when they are measured in their local currencies rather than under a common currency, i.e., USD/USD and EUR/EUR, respectively. Particularly, during periods 26 and 27, there is a larger probability of cointegration between the EURO STOXX 50 and S&P 500 when they are measured in local currency terms. Furthermore, the EURO STOXX 50 appears to cointegrate more strongly with the S&P 500 during periods 31 and 44 when they are measured in USD/USD and local currency terms, yet the evidence of cointegration is weaker under EUR/EUR (note the depreciation of the EUR against the USD during these periods). Besides, Fig. 3.5 reveals that during period 40, the evidence that the EURO STOXX 50 cointegrates with the S&P 500 is significant only when it is measured in EUR/EUR and the local currencies, while no cointegration appears under USD/USD. On the other hand, as for the evidence of the S&P 500 cointegrating with the EURO STOXX 50, during periods 26, 31, 34, 41, 45, 46–48 and 51, we observe stronger cointegration when they are measured in local currency terms.



(a) EURO STOXX 50's cointegration with S&P 500 measured in USD

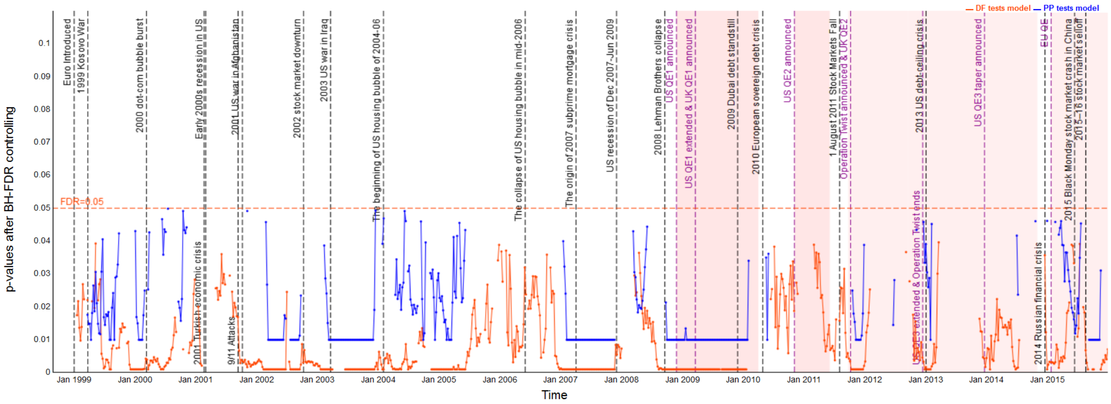


(b) EURO STOXX 50's cointegration with S&P 500 measured in GBP

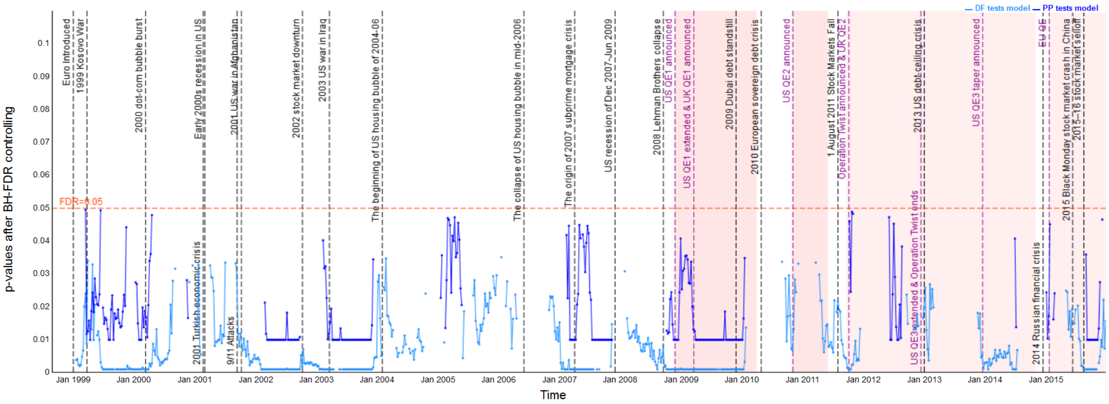


(c) EURO STOXX 50's cointegration with S&P 500 measured in local currencies

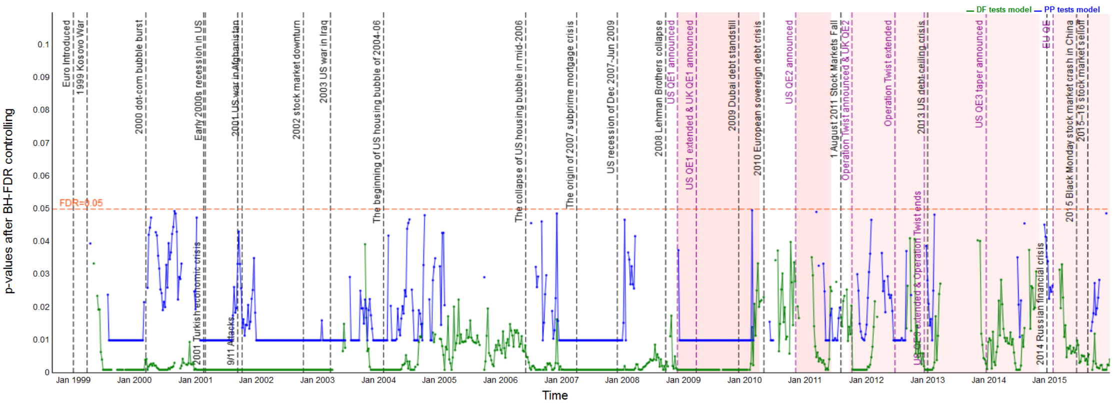
Fig. 3.5. Dynamic p-values (based on DF and PP tests models) after BH FDR controlling showing EURO STOXX 50's cointegration with S&P 500 in USD, EUR and local currency terms, during 1998–2015. The red horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1998–2015; red shading represents implementation of QE policies.



(a) S&P 500 100's cointegration with EURO STOXX 50 measured in USD



(b) S&P 500 100's cointegration with EURO STOXX 50 measured in GBP



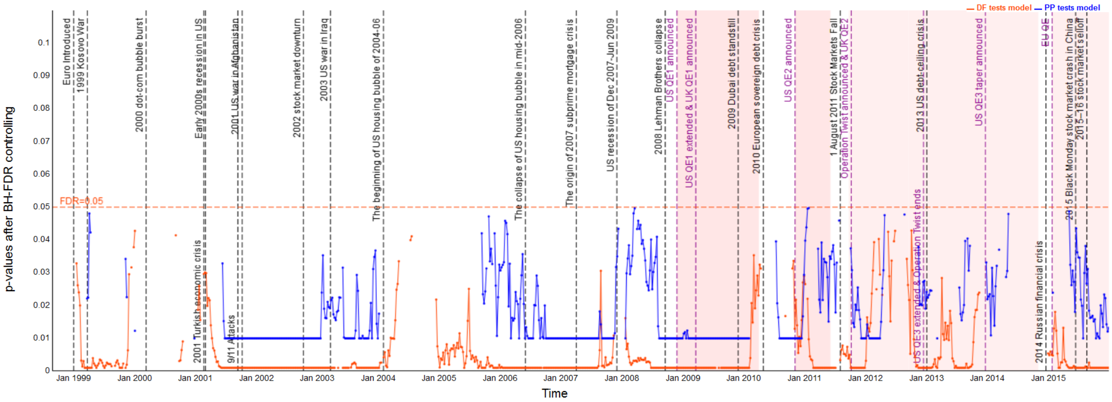
(c) S&P 500 100's cointegration with EURO STOXX 50 measured in local currencies

Fig. 3.6. Dynamic p-values (based on DF and PP tests models) after BH FDR controlling showing S&P 500 100's cointegration with EURO STOXX 50 in USD, EUR and local currency terms, during 1998–2015. The red horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1998–2015; red shading represents implementation of QE policies.

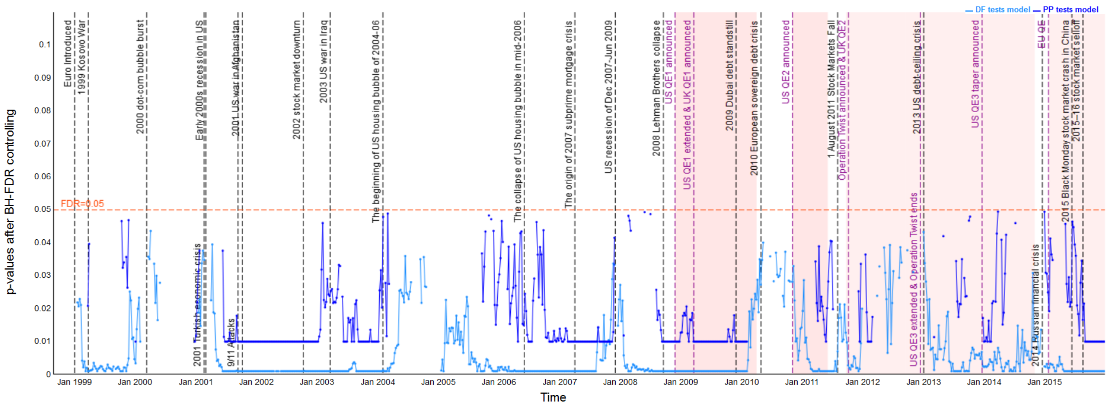
3.6.3 Dynamic Cointegration between the FTSE 100 and EURO STOXX 50 Indices

Figs. 3.7 and 3.8 display the dynamic *p*-values based on both DF and PP tests of residuals indicating the extent to which the EURO STOXX 50 cointegrates with the FTSE 100 and vice versa, measured in both common and local currency terms, for 1998–2015. Table 3.5 shows all the periods of integration at both 1% and 5% statistical significance levels. Table 3.5 reports that the periods during which the EURO STOXX 50 cointegrates with the FTSE 100 and the FTSE 100 cointegrates with the EURO STOXX 50 are quite similar during the whole sample period. In particular, for periods 31–39, there is the strongest probability of cointegration existing between the FTSE 100 and EURO STOXX 50, out of the entire sample period. We also observe that the FTSE 100 cointegrates with the EURO STOXX 50 only during periods 24 and 40, while there is no evidence that the EURO STOXX 50 cointegrates with the FTSE 100. The reason might be related to the severe debt crisis in the Eurozone, which led to more shocks moving from the Eurozone to the UK stock market than vice versa. In addition, since the EURO STOXX 50 index covers 50 stocks from 11 Eurozone countries (i.e., Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain), it appears that the collapse of the dot-com asset bubble in the US in March 2000 affected the EURO STOXX 50 more than the FTSE 100 index.

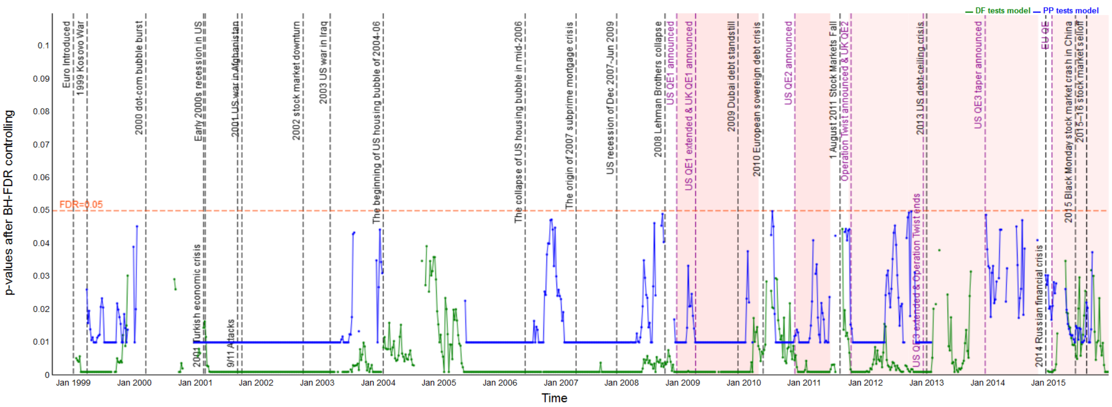
Regarding the influence of exchange rate movements, Table 3.5 reports the cointegration between the FTSE 100 and the EURO STOXX 50. Of particular note, during periods 40 and 45, we identify stronger cointegration of the EURO STOXX 50 with the FTSE 100 and vice versa when using the local currencies. Furthermore, during periods 46–48, i.e., the US Fed implemented the QE3 and tapering policies, there is strong persistent cointegration of the FTSE 100 and EURO STOXX 50. These results indicate that the economic recession in the UK and Eurozone markets and a series of similar monetary and fiscal policies caused these two markets to integrate significantly.



(a) EURO STOXX 50's cointegration with FTSE 100 measured in GBP

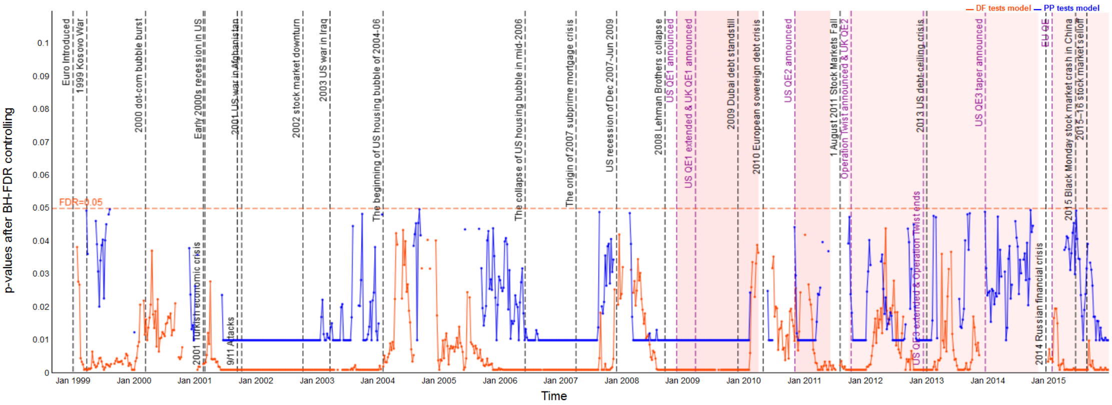


(b) EURO STOXX 50's cointegration with FTSE 100 measured in EUR

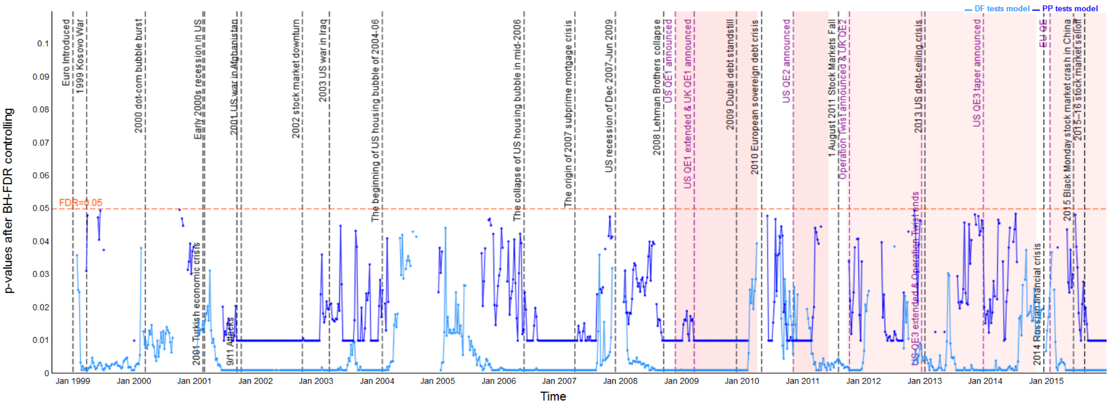


(c) EURO STOXX 50's cointegration with FTSE 100 measured in local currencies

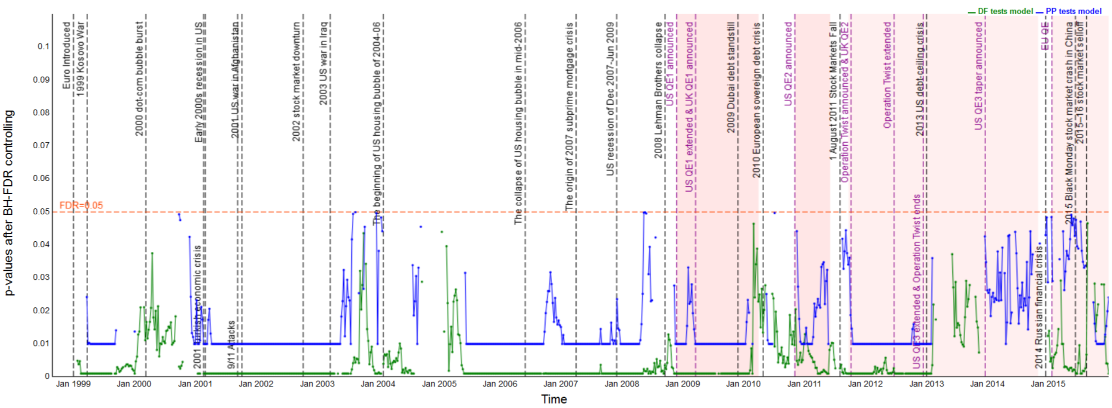
Fig. 3.7. Dynamic p-values (based on DF and PP tests models) after BH FDR controlling showing EURO STOXX 50's cointegration with FTSE 100 in GBP, EUR and local currency terms, during 1998–2015. The red horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1998–2015; red shading represents implementation of QE policies.



(a) FTSE 100's cointegration with EURO STOXX 50 measured in GBP



(b) FTSE 100's cointegration with EURO STOXX 50 measured in EUR



(c) FTSE 100's cointegration with EURO STOXX 50 measured in local currencies

Fig. 3.8. Dynamic p-values (based on DF and PP tests models) after BH FDR controlling showing FTSE 100's cointegration with EURO STOXX 50 in GBP, EUR and local currency terms, during 1998–2015. The red horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1998–2015; red shading represents implementation of QE policies.

To sum up, based on the dynamic cointegration analysis between all pairs of stock market indices, we conclude that the persistent cointegration periods observed are associated with asset bubbles, market crashes, sovereign failures, or wars. In particular, during 2007–09 global financial crisis, all three major stock markets exhibited the most persistent and deepest cointegration with each other due to the serious shocks on the US and global stock markets based on both DF and PP tests. There is some evidence that, during economic, financial and political shocks, the capitalization of the stock market indices grew quickly and synchronously, and they were highly cointegrated with each other. Meanwhile, when an individual stock market experiences economic, financial and political episodes (e.g., see 2004–06 US housing asset bubble, the 2010 European sovereign debt crisis, etc.), it is significantly affected by other stock markets due to the recession in the former country's economy. Furthermore, by comparing with the dynamic correlation between S&P 500 and FTSE 100, S&P 500 and EURO STOXX 50, FTSE 100 and EURO STOXX 50, the degree of cointegration changed associated with the rising or decreasing correlation obviously. Additionally, when the indices are measured in local currency terms, the probability of cointegration between all three pairs of stock indices is higher than that when using the same unit of currency for each index in the pair, which is consistent with the findings of Voronkova's study [77]. Evidence of cointegration can only be found when using local currencies during some time periods, which is in line with Alexander and Thillainathan [76], who also found that integration between international equity markets appeared only when stock indices were expressed in local currency terms. Our comparative analysis conducted under common and local currency terms, formulated on a dynamic framework, provides new insights over and above that found in the existing studies.

Table 3.4. The observed periods of cointegration and Granger causality (in long run) between the S&P 500 and EURO STOXX 50, during 1998–2015.

S&P 500 vs. EURO STOXX 50	**Observed periods**		
S&P 500 → EURO STOXX 50	USD/USD	EUR/EUR	EUR/USD
At 1% significance level	periods 22, 23, 27–39	periods 22–24, 27–30	periods 23–29, 31–39
	periods 41–44	periods 32–39,	periods 41–44, 46–50
	periods 49, 52–53	periods 41, 52–53	periods 52–53
At 5% significance level	periods 24–26, 46–48	periods 25, 26, 31, 40	periods 30, 40, 45
	periods 50–51	periods 42–48, 50–51	periods 51
S&P 500 causes EURO STOXX 50	periods 22–23, 27–34	periods 22–23, 25	periods 22–23, 25
	periods 38–39, 41	periods 27–34, 40–41	periods 27–36, 38–39, 41
	periods 49–53	period 49–51	periods 50–51
(32 sub-periods)	(56%)	(50%)	(56%)
EURO STOXX 50 → S&P 500	USD/USD	EUR/EUR	USD/EUR
At 1% significance level	periods 23, 24, 27–31, 33	periods 22–24, 27–30	periods 23–39
	periods 35–39, 42, 44	periods 33, 35–39, 44	periods 41, 43–49
	periods 46–53	periods 46–48, 52–53	periods 50–51
At 5% significance level	periods 22, 25, 26, 32	periods 25, 26, 31, 34	periods 40, 42
	periods 34, 40, 41	periods 40, 41, 49–51	
EURO STOXX 50 causes S&P 500	periods 24–25,27–28, 31	periods 24–25, 27–28, 31	periods 24–28, 31
	periods 35–36, 40, 42–44	periods 35–36, 38–39	periods 40, 42–44
	periods 46–51	periods 42–44, 46–49	periods 46–49, 52–53
(32 sub-periods)	(53%)	(50%)	(50%)

Note that, to indicate that A cointegrates with B, we write $B \to A$.

Table 3.5. The observed periods of cointegration and Granger causality (in long run) between the FTSE 100 and EURO STOXX 50 during 1998–2015.

FTSE 100 vs. EURO STOXX 50	**Observed periods**		
FTSE 100 → EURO STOXX 50	GBP/GBP	EUR/EUR	EUR/GBP
At 1% significance level	periods 22, 23, 26–39	periods 22, 23, 26–39	periods 22, 23, 26–39
	periods 41–44, 46–53	periods 41–44, 46–53	periods 41–48, 52–53
At 5% significance level	period 40	period 40	periods 40, 50–51
FTSE 100 causes EURO STOXX 50	periods 22–23, 29–31, 33	periods 22, 29–30, 33–34	periods 22–23, 29–31
	periods 35–36, 39, 41	periods 40–41	periods 33–34, 36, 41
	periods 50–51, 52–53	periods 50–53	periods 50–53
(32 sub-periods)	44%	34%	47%
EURO STOXX 50 → FTSE 100	GBP/GBP	EUR/EUR	GBP/EUR
At 1% significance level	periods 22, 23, 25–39	periods 22, 23, 25–39	periods 22, 23, 25–39
	periods 41, 44–53	periods 41, 44–53	periods 41–46, 49–53
At 5% significance level	periods 24, 40, 42	periods 24, 40, 42	periods 24, 40, 48
EURO STOXX 50 causes FTSE 100	periods 24, 26–28, 34	periods 27–28, 36	periods 24–28, 31
	periods 40, 44	periods 40, 44	periods 43, 45–46
	periods 46–48	periods 46–48	periods 50–51
(32 sub-periods)	31%	25%	34%

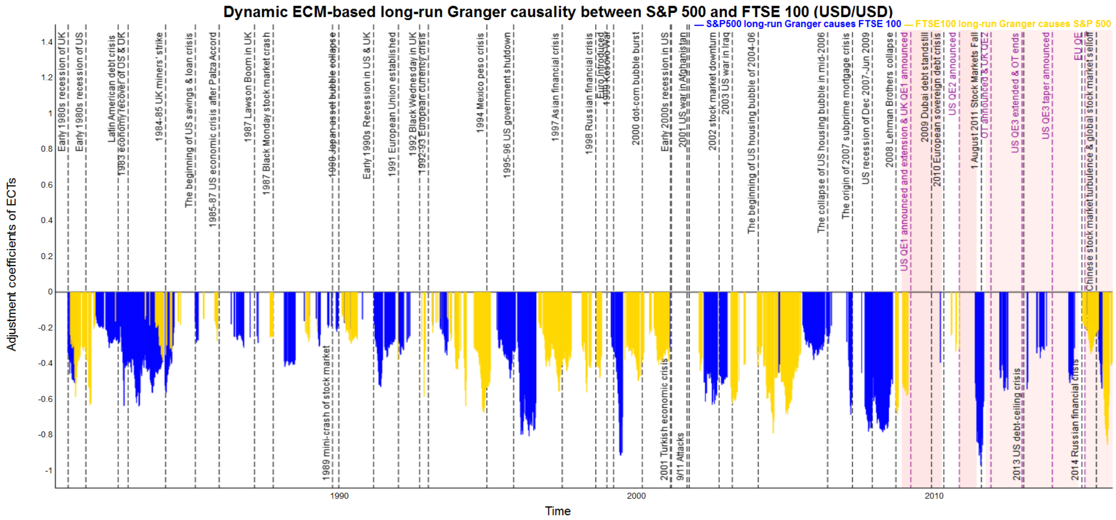
Note that, to indicate that A cointegrates with B, we write $B \to A$.

3.7 ECM-based Long-run Granger Causality Analysis

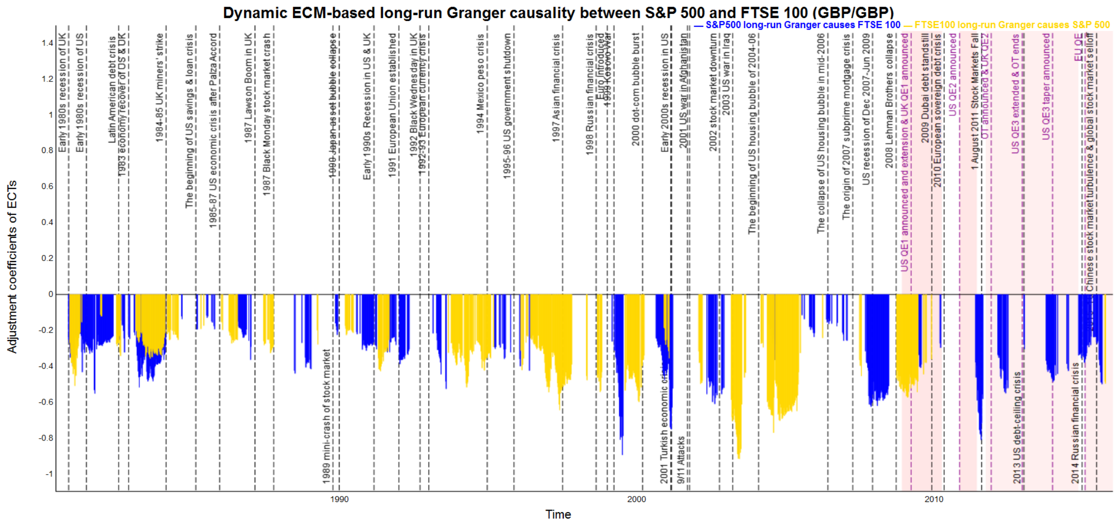
As was described in the previous subsection, the dynamic p-values based on DF and PP tests after BH-FDR controlling indicate the probability that we can accept the long-run cointegration between the pairs of stock market indices. Then, the ECM is used to identify the long-run Granger causality through the error correction coefficients. Only statistical significant error correction coefficients are reported in Figs. 3.9 to 3.11 for each pair of stock market indices of S&P 500, FTSE 100 and EURO STOXX 50 from 1980 to 2015, respectively. In particular, Tables 3.3–3.5 report the time periods in which we observe the statistical significantly directional Granger causality between each pair of stock indices in the long run during 1980–2015. Table 3.6 provides the summary statistics in the form of strongest, weakest, and average absolute value of adjustment coefficients.

In the case of the long-run Granger causality between S&P 500 and FTSE 100, Figs. 3.9(a)–3.9(c) show the dynamic statistical significant error correction coefficients based on the results of the FTSE 100's cointegration with the S&P 500 and the S&P 500 cointegration with the FTSE 100, calculated using the same and local currencies, respectively. We observe that all the adjustment coefficients for the ECTs are negative for S&P 500 and FTSE 100, confirming the long-run Granger causality running from S&P 500 towards FTSE 100 (shown with a blue bar), from FTSE 100 to S&P 500 (shown with a yellow bar), respectively. As shown in Table 3.3, the proportion of period in which the S&P 500 long-run Granger causes FTSE 100 is greater than the reverse, namely 53% to 42% when using USD/USD, 53% to 42% when using GBP/GBP, and 55% to 34% when using the local currencies. Specifically, the time periods in which FTSE 100 is strongly long-run Granger caused by S&P 500, namely periods 1–4, 13, 23, 33–34, all accompany economic recession or financial shocks in the US market, whether we measure them in common or local currency terms. In contrast, the significant negative error correction coefficients are found as an evidence of long-run Granger causality running from FTSE 100 to S&P 500 during periods 1, 4, 15–16 40, i.e., early 1980s recession in the UK, UK market's "Black Wednesday" currency crisis in 1992, and the subsequent 1992–93 European currency crisis, significantly Granger caused the US stock market in the long run. Furthermore, significantly directional long-run Granger causality between S&P 500 and FTSE 100 are found during the early 1980s recession in the US and UK, following the 1993 economic recovery of US and UK, the early 1990s recession in the US and UK (only using GBP/GBP and local currencies), the early 2000s recession in the US (only using GBP/GBP and local currencies). Meanwhile, the statistical results in Table 3.6 show that the dynamic error correction coefficients vary over time. In most of the time periods, the coefficients that show evidence of long-run Granger causality running from S&P 500 to FTSE 100 are stronger than the reverse direction, when measured in USD/USD (average values of 0.387 vs. 0.366) and local currencies (average values of 0.429 vs. 0.377), which indicates that the US stock market is more influential than the UK market. However, contrasting results are found when we use GBP/GBP (average values of 0.336 vs. 0.349). Moreover, the strongest coefficients for the S&P 500 long-run Granger causes FTSE 100 is 0.970 (using USD/USD during period 42), 0.895 (using GBP/GBP during period 42), and 0.926 (using USD/GBP during period 34). It should be noted that since the high volatility during the August 2011 stock market fall and 2007–09 global financial crisis, the shock of US stock market exerts a significant leadership toward UK market.

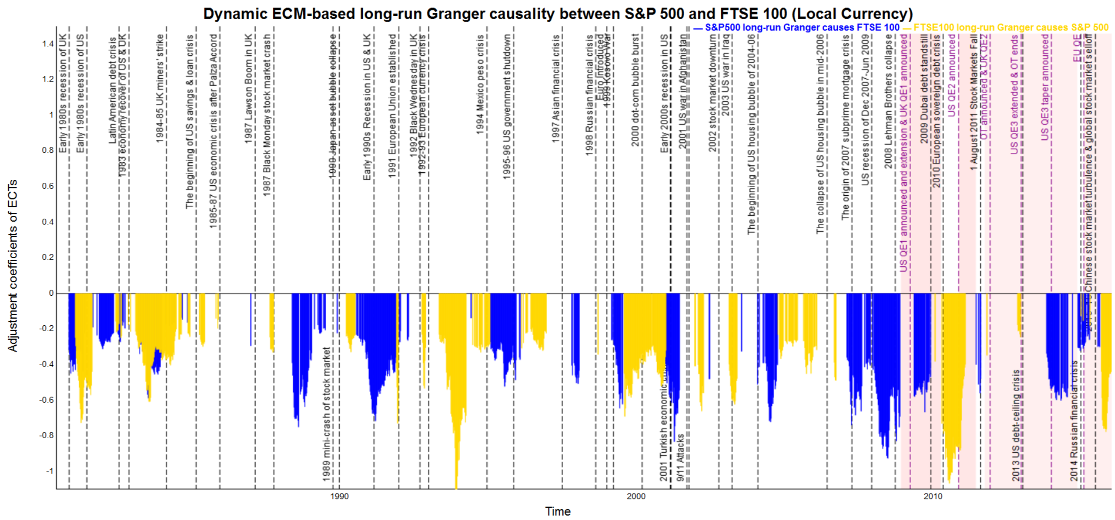
The statistical significant and negative adjustment coefficients for S&P 500 and EURO STOXX 50 in Fig. 3.10(a)–3.10(c) provide evidence of long-run causal relationship running for S&P 500 to EURO STOXX 50 (shown with a blue bar), from EURO STOXX 50 to S&P 500 (shown with a yellow bar) from 1998 to 2015 calculated using the same and local currencies, respectively. From Table 3.4, we find that the proportion of period in which the S&P 500 long-run Granger causes EURO STOXX 50 is stronger than the reverse, namely 56% to 53% when using USD/USD and 50% to 50% when using EUR/EUR, and 56% to 50% measured in the local currencies. Furthermore, the time periods in which the S&P 500 strongly long-run Granger causes EURO STOXX 50 is particularly during the 1999 Kosovo war, the 2002 stock market downturn, the collapse of the US housing bubble, the 2007–09 global financial crisis, the 2010 European debt crisis, the 2015–16 US stock market sell-off, all of which are accompanied by economic, financial or political shocks in the US market. However, the reverse direction that EURO STOXX 50 long-run Granger causes S&P 500 is observed during the burst of the 2000 dot-com bubble, the beginning of US housing bubble period, from the early 2000s recession in the US to the 9/11 attack and war in Afghanistan, the beginning period of the US housing price bubble, the 2010 European debt crisis, the period that second round of QE implementation in the UK. It should be noted that, when measured in EUR/EUR, there is strongly long-run Granger causality running from the EURO STOXX 50 to S&P 500 after the Lehman Brother collapse in Sept. 2008 since the significant depreciation of Euro against US dollars, resulting in money inflows and investment shock in the Eurozone stock markets and causes changes in S&P 500. Moreover, Table 3.6 displays the average error correction coefficients between the S&P 500 and EURO STOXX 50, using both the same and local currency terms, and the findings further prove that the long-run Granger causality between S&P 500 EURO STOXX 50 is similar, with average values of 0.441 vs. 0.416 in USD/USD, 0.339 vs. 0.368 in EUR/EUR and 0.504 vs. 0.511 in USD/EUR, respectively. The maximum error correction coefficients for the S&P 500's causes EURO STOXX 50, 1.668 using USD/USD in period 39, 1.407 using EUR/EUR in period 29, and 1.332 using local currencies in period 29, are associated with the 2009 Dubai debt standstill and the 2002 stock market downturn.



(a) Dynamic long-run Granger causality between S&P 500 and FTSE 100 measured in USD

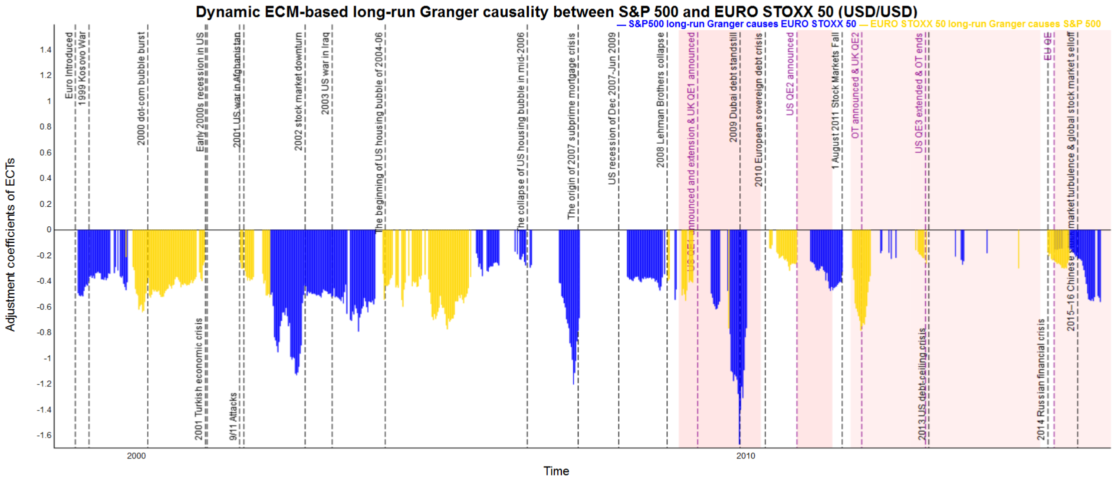


(b) Dynamic long-run Granger causality between S&P 500 and FTSE 100 measured in GBP

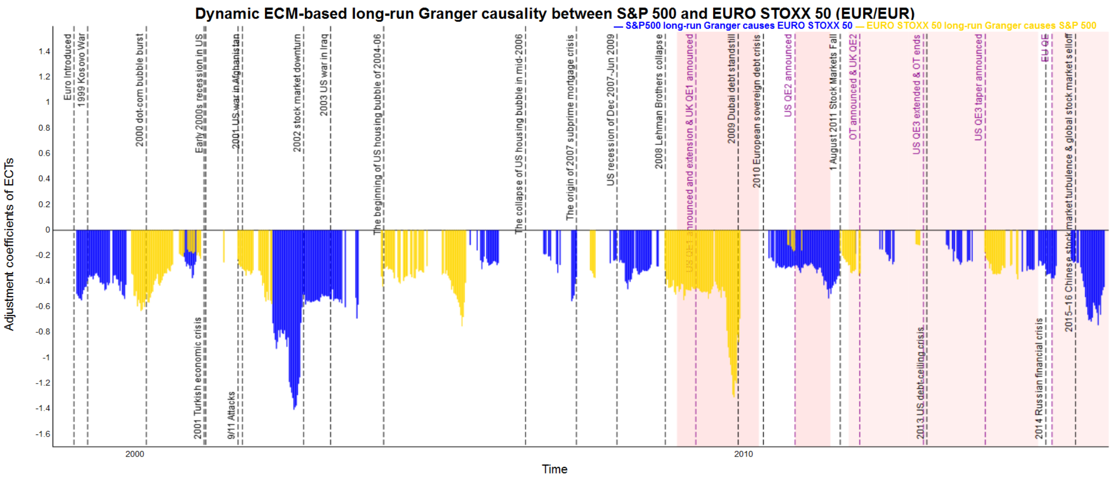


(c) Dynamic long-run Granger causality between S&P 500 and FTSE 100 measured in local currencies

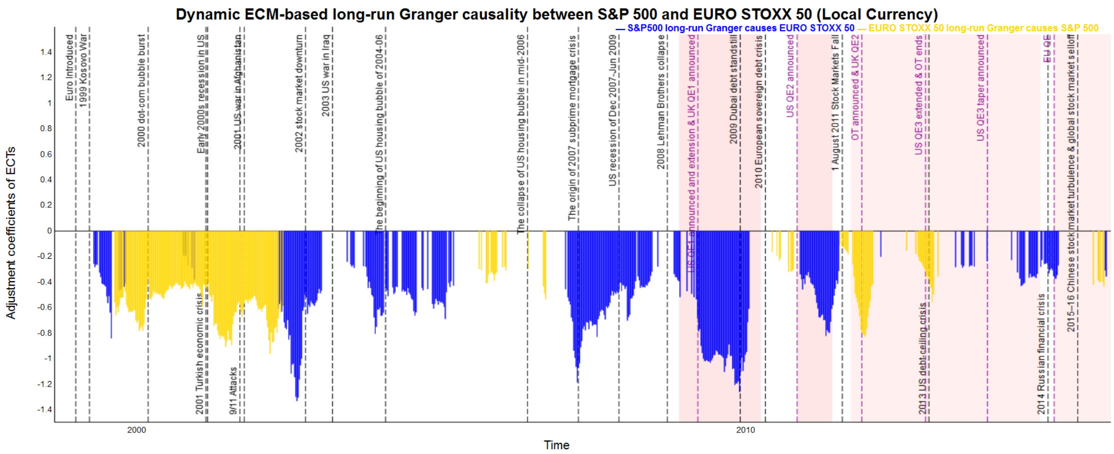
Fig. 3.9. The statistical significant and negative dynamic ECM-based long-run Granger causality of S&P 500 and FTSE 100 measured in common and local currency terms in 1980–2015. The blue bars show the S&P 500 causes FTSE 100, and the yellow bars show the FTSE 100 causes S&P 500, respectively. The red shading represents implementation of QE policies.



(a) Dynamic long-run Granger causality between S&P 500 and EURO STOXX 50 measured in USD

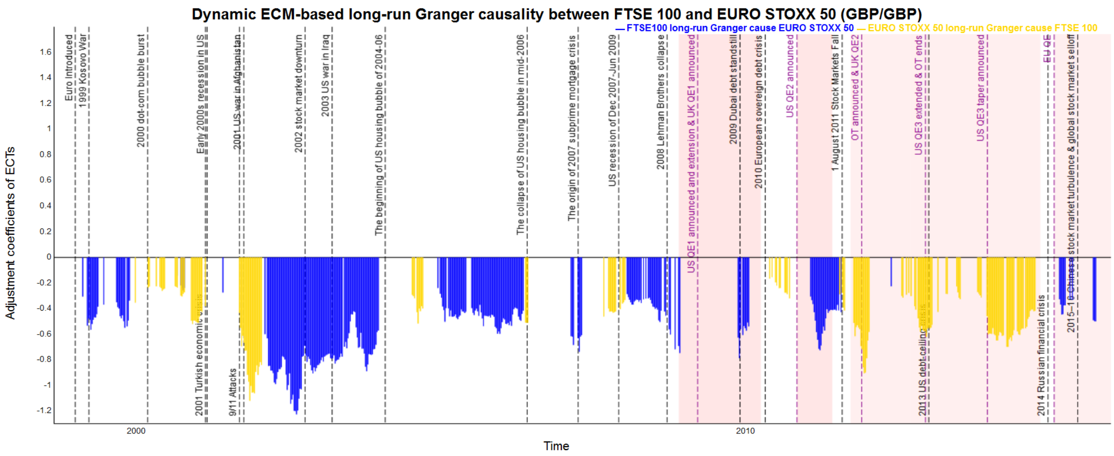


(b) Dynamic long-run Granger causality between S&P 500 and EURO STOXX 50 measured in EUR

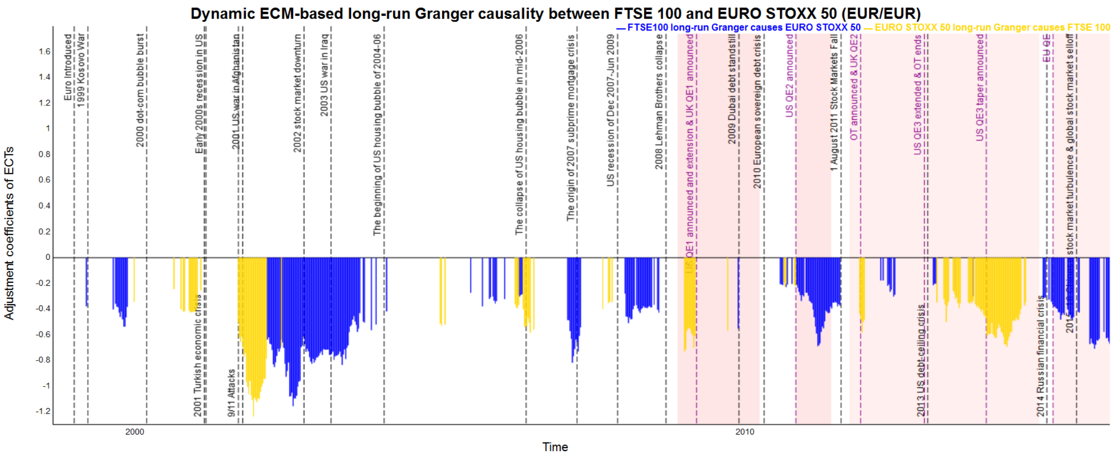


(c) Dynamic long-run Granger causality between S&P 500 and EURO STOXX 50 measured in local currencies

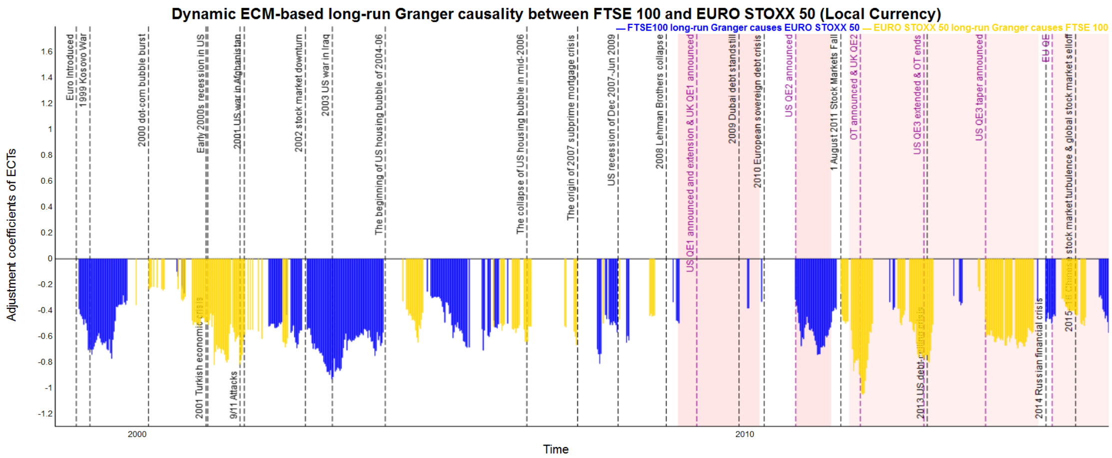
Fig. 3.10. The statistical significant and negative dynamic ECM-based long-run Granger causality of S&P 500 and EURO STOXX 50 measured in common and local currency terms in 1998–2015. The blue bars show the S&P 500 causes EURO STOXX 50, and the yellow bars show the EURO STOXX 50 causes S&P 500, respectively. The red shading represents implementation of QE policies.



(a) Dynamic long-run Granger causality between FTSE 100 and EURO STOXX 50 measured in GBP



(b) Dynamic long-run Granger causality between FTSE 100 and EURO STOXX 50 measured in EUR



(c) Dynamic long-run Granger causality between FTSE 100 and EURO STOXX 50 measured in local currencies

Fig. 3.11. The statistical significant and negative dynamic ECM-based long-run Granger causality of FTSE 100 and EURO STOXX 50 measured in common and local currency terms in 1998–2015. The blue bars show the FTSE 100 causes EURO STOXX 50, and the yellow bars show the EURO STOXX 50 causes FTSE 100, respectively. The red shading represents implementation of QE.

Finally, Fig. 3.11(a)–3.11(c) show the estimation of dynamic adjustment coefficients for the ECM-based long-run Granger causality for FTSE 100 and EURO STOXX 50, from 1998 to 2015 in both common and local currency terms, respectively. The statistical significant and negative adjustment coefficients provide an evidence of long-run Granger causal relationship running for FTSE 100 to EURO STOXX 50 (shown with a blue bar), from EURO STOXX 50 to FTSE 100 (shown with a yellow bar) respectively. As shown in Table 3.5, the proportion of period in which the FTSE 100 long-run Granger causes EURO STOXX 50 is much more compared with the causality running from EURO STOXX 50 to FTSE 100, namely 44% to 31% when using GBP/GBP, 34% to 25% when using EUR/EUR and 47% to 34% with local currency terms. Moreover, the time periods in which the FTSE 100 strongly long-run Granger causes EURO STOXX 50 are especially during the 1999 Kosovo war, the 2002 stock market downturn, the collapse of US housing bubble, the 2007–09 global financial crisis, the 2010 European debt crisis, the US recession of Dec 2007Jun 2009, the US QE2 from November 3th, the 2010 to June 30th, 2011, the 2015–16 US stock market selloff. However, the reverse Granger causal direction that EURO STOXX 50 long-run Granger causes FTSE 100 is during the 9/11 Attacks, the 2001 US war in Afghanistan, the August 2011 US stock market fall, during the 2013 US debt-ceiling crisis, the implementation of US QE3 and tapering announced and UK QE2, respectively. Next, from the average error correction coefficients between the FTSE 100 and EURO STOXX 50 shown in Table 3.6, we notice that the EURO STOXX 50 long-run Granger causes FTSE 100 is slightly stronger than the reverse direction, with average values of 0.498 vs. 0.425 (GBP/GBP), 0.479 vs. 0.504 (EUR/EUR), and 0.553 vs. 0.524 (local currency terms). The strongest coefficients by which the long-run Granger causality running from FTSE 100 to EURO STOXX 50 is 1.225 (with GBP/GBP in period 29), 1.154 (with EUR/EUR in period 29) and 0.930 (with local currency terms in period 29). What is more, the strongest coefficients of the EURO STOXX 50 long-run Granger causality FTSE 100 are 1.119 (with GBP/GBP in periods 27–28), 1.233 (with EUR/EUR in periods 27–28), and 1.050 (with local currency terms in period 42). The results reveal that since the various bilateral trade and economic cooperation agreements exist between the US, UK and the Eurozone markets, the 9/11 attack, the 2001 US war in Afghanistan, and the August 2011 stock market fall resulting in significantly long-run Granger causal relation between FTSE 100 and EURO STOXX 50.

Table 3.6. Statistical Analysis of Dynamic Error Correction Coefficients (absolute value) of ECTs.

Stock Market Indices	**Strongest Coeff**	**Weakest Coeff**	Average Coeff
S&P 500 vs. FTSE 100			
S&P 500 causes FTSE 100 (USD/USD)	0.970	0.124	0.387
FTSE 100 causes S&P 500 (USD/USD)	0.856	0.120	0.366
S&P 500 causes FTSE 100 (GBP/GBP)	0.895	0.116	0.336
FTSE 100 causes S&P 500 (GBP/GBP)	0.917	0.113	0.349
S&P 500 causes FTSE 100 (GBP/USD)	0.926	0.136	0.429
FTSE 100 causes S&P 500 (USD/GBP)	1.284	0.141	0.377
S&P 500 vs. EURO STOXX 50			
S&P 500 causes EURO STOXX 50 (USD/USD)	1.668	0.141	0.441
EURO STOXX 50 causes S&P 500 (USD/USD)	0.783	0.157	0.416
S&P 500 causes EURO STOXX 50 (EUR/EUR)	1.407	0.115	0.339
EURO STOXX 50 causes S&P 500 (EUR/EUR)	1.308	0.109	0.368
S&P 500 causes EURO STOXX 50 (EUR/USD)	1.332	0.191	0.504
EURO STOXX 50 causes S&P 500 (USD/EUR)	0.963	0.122	0.511
FTSE 100 vs. EURO STOXX 50			
FTSE 100 causes EURO STOXX 50 (GBP/GBP)	1.225	0.143	0.498
EURO STOXX 50 causes FTSE 100 (GBP/GBP)	1.119	0.154	0.425
FTSE 100 causes EURO STOXX 50 (EUR/EUR)	1.154	0.177	0.479
EURO STOXX 50 causes FTSE 100 (EUR/EUR)	1.233	0.191	0.504
FTSE 100 causes EURO STOXX 50 (EUR/GBP)	0.930	0.091	0.553
EURO STOXX 50 causes FTSE 100 (GBP/EUR)	1.050	0.215	0.524

3.8 Summary Results of Dynamic Correlation, Cointegration and ECM-based long-run Granger Causality Analysis

From the results of dynamic correlation, cointegration and ECM-based long-run Granger causality analysis between the S&P 500 and FTSE 100, S&P 500 and EURO STOXX 50, and FTSE 100 and EURO STOXX 50 over 1980–2015 in both common and local currencies terms, the following similarities are derived. As shown in Fig. 3.2, and Figs. 3.3–3.8, the dynamic correlation and cointegration analysis between all pairs of stock market indices become stronger and more deeply integrated with each other when they are associated with economic, financial and political shocks. However, the decreasing, weaker correlation and cointegration evolving over time have been found during the bull market or the recovery of the stock market after serious shocks. Specifically, identifying the similarities between dynamic correlation and ECM-based long-run Granger causality provides more interesting results not only for the interaction detection but also for the directed causal relations.

The dynamic correlation analysis highlights the interactions between US and UK stock markets tend to increase significantly during 1) the early 1980s recession of the US, the 198485 UK miners' strike, the 1990 Gulf War, both associated with bidirectional long-run Granger causality running between US and UK stock markets; 2) the 1987

"Black Monday" stock market crash, the 2002 stock market downturn, the 2007 subprime mortgage crisis, the 2011 US debt-ceiling crisis, associated with long-run Granger causality running from the S&P 500 to FTSE 100; 3) the 199293 European currency crisis, before the 1997 Asian financial crisis, with long-run Granger causality running from FTSE 100 to S&P 500. In contrast, the significantly decreasing correlation between S&P 500 and FTSE 100 are observed during 1) the 1982 economic recovery of the US and the UK, the 1994 Mexico peso crisis, accompanied with long-run Granger causality running from the US to the UK stock market; 2) the 199293 European currency crisis, the period of the US Dot-com bubble, the period of 2004–2006 US housing price bubble, with long-run Granger causality running from the UK to the US stock market.

In terms of the correlation dynamics across the US and Eurozone stock markets tend to increase significantly during: 1) the bear market between post 2001 and 2003, the US recession from December 2007 to post 2008, the Lehman brother collapse in September 2008, the 2015-16 US stock market sell-off, associated with long-run Granger causality running from the S&P 500 to the EURO STOXX 50; while during: 2) the 2000 dot-com bubble burst, the beginning of US housing bubble from 200405, the August 2011 stock market fall, all associated with long-run Granger causality running from the EURO STOXX to the S&P 500. In contrast, we can observe the gradually decreasing correlation during the periods after the introduction of Euro and the 1999 Kosovo war, the beginning of 2007, both associated with significant magnitude of long-run Granger causality from the S&P 500 to the EURO STOXX 50; while long-run Granger causality from the EURO STOXX 50 to the S&P 500 during the second round of US QE policy implementation.

By observing the dynamic correlation and ECM-based long-run Granger causality of the FTSE 100 and EURO STOXX 50, all increasing correlation accompanied with significantly stronger long-run Granger causality in both direction during 1) the bear market between post 2001 and 2003 with FTSE 100 long-run Granger causes EURO STOXX; 2) the 9/11 Attack, the 2001 US war in Afghanistan and the August 2011 stock market fall with significantly long-run Granger causality running from the EURO STOXX 50 to the FTSE 100. On the contrary, the decreasing correlation associated with direction causal relations during the introduction of the Euro, the 1999 Kosovo war and the 200506 US housing price bubble, the US QE2, the EU QE during 201516, both associated with long-run Granger causality running from the FTSE 100 to the EURO STOXX 50, respectively. However, during the implementation of QE in the US (QE3 and tapering policies announced), the EURO STOXX 50 significantly long-run Granger causes the FTSE 100 with decreasing correlation.

We summary the similarities and differences between dynamic correlation, cointegration and ECM-based long-run Granger causality analysis of each pair of developed stock markets of the US, UK and Eurozone as follows:

- During the periods of economic, financial and political episodes, the degree of dynamic correlation, cointegration and ECM-based long-run Granger causality between the pairs of stock market indices increased significantly in all cases. However, during the bull market and recovery period of the stock market after shocks, the correlation decreased gradually associated with weaker integration and long-run Granger causality. In particular, there is stronger and more significant interactions, Granger causal relations between the stock market indices when they are both measured in local currency terms.

- The dynamic correlation analysis ascertains the degree of co-movement between stock markets based on synchronous changes, which might miss long-run relationships occurring on a long time-scale. Since the cointegration tests capture the long-run equilibrium relations between two stock market indices that are cannot deviate too far away from each other in the long term, the dynamic cointegration between pairs of stock markets is more persistent than the dynamic correlation associated with economic, financial and political episodes. Furthermore, the ECM tests to examine whether returns of one market influence another based on the existed long-run cointegration, which could reflect the direction of the long-run Granger causality between stock market indices efficiently.

Finally, the understanding of the dynamic *integration* and *causality* between the various national stock markets is important since it has a direct impact on investors' investment strategy particularly those that involves cross-border investments. A combination of not perfectly correlated stock markets gives the investor an opportunity to gain from portfolio diversification. For investors with longer time horizons, the benefit of international diversification can be attained if one country's stock market is not cointegrated with other country's stock market [17]. However, our empirical findings indicate that the presence of the increasing correlation, cointegration and long-run Granger causality between the local stock markets with foreign stock markets during the economic, financial and political shocks, may limit potential portfolio diversification benefits in the sample stock markets.

3.9 Conclusions

In this chapter, by combining the rolling-window technique with correlation, cointegration and ECM tests, we explore the dynamic *integration* and *causality* between each pair of US, UK, and Eurozone stock markets from January 1980 to December 2015 under the impact of a series of economic, financial and political shocks. Specifically, we measure those time-varying symmetric and asymmetric interactions under the same currencies and under local currencies to comprehensively analyze how the exchange rates fluctuation affects the integration and linkages between stock market indices over time. Besides, the similarity and difference between the integration and causality are studied.

The findings obtained indicate that the degree of short-term correlation, long-term cointegration and ECM-based long-term Granger causality between all pairs of stock market indices both changed over time. Especially, stronger interactions and causality when measured in local currency terms than used in common currencies. The dynamic correlation analysis ascertains the degree of co-movement between the US, UK and Eurozone stock markets based on stationary returns, and highlights the interactions between stock markets tend to increase during economic, financial and political shocks over 1980–2015. However, decreasing correlations were found during the bull market and the recovery of the stock market after the shocks. Similarly, the existence of long-run cointegration between each pairwise of stock markets is more significant during times of economic, financial and political episodes, whereas the weaker cointegration varied over time has been found during the bull market or the recovery of the stock market after those "extreme events". In particular, the strongest and most persistent cointegration exists between US, UK and Eurozone stock markets are during 2007–09 global financial crisis.

Furthermore, the ECM-based long-run Granger causality which exacts from the existed cointegration relationships reveals the directed dynamic causal relation between pairwise stock markets of US, UK and Eurozone from 1980 to 2015. Specifically, we found that associated with increasing correlation evolved with time, the US stock market long-run Granger caused the UK and Eurozone markets during the economic, financial and political episodes happened in the US market, for example, during the 1987 "Black Monday" stock market crash, the 2002 stock market downturn, the 2007 sub-prime mortgage crisis and the Lehman Brother collapse in September 2008, etc. In contrast, the UK and Eurozone markets cause the US market especially during 1992–93 European currency crisis, the 2000 dot-com bubble burst and the beginning of the US housing bubble from 2004–05, etc. In particular, there is significantly stronger long-run Granger causality from the UK to Eurozone markets during the bear market between post 2001 and 2003, meanwhile, Eurozone stock markets lead UK market during the periods of the 9/11 Attack, the 2001 US war in Afghanistan and the August 2011 stock market fall all accompanied with increasing correlation, respectively. On the other hand, with the decreasing correlation over time, the US market has remained dominant in leading the information transmission to UK and Eurozone markets during the 1982 economic recovery of US and UK, the 1994 Mexico peso crisis, the periods after introduced the Euro, the 1999 Kosovo war and the beginning of 2007. However, we find the unidirectional causality from the UK, Eurozone markets to the US market during 1992–93 European currency crisis, the period of the US Dot-com bubble, the period of 2004–06 US housing price bubble and the US QE2 policy implementation. The obtained results further show that during the introduction period of Euro, the 1999 Kosovo war, the 2005–06 US housing price bubble, the US QE2, the EU QE during 201516, there is long-run Granger causality from UK to Eurozone markets, while the reverse causality could be observed during the implementation of QEs in the US (QE3 and tapering announced).

To conclude, our results suggest that the potential for diversifying risk by investing in the US, UK, and Eurozone stock markets is limited during the periods of economic, financial and political shocks. Testing for cointegration and any changes in it over time is crucial since, if cointegration does not hold, it indicates that the markets are not linked and no Granger causality in the long run and therefore it is possible to gain from diversification. As for the dynamic correlation, the lower correlation between pairs of stock markets will be beneficial to investors.

Chapter 4

Modelling the Short-run Error Adjustment Effects and Long-run Cointegration of the International Stock Market based on Complex Network Theory

Abstract: This chapter examines the short-run error adjustment mechanisms and long-run equilibrium relationships between the global stock markets within the MSCI ACWI countries/regions over the period of January 2007–June 2017. Through the cointegration-based error correction models and network analysis approach, we build up static and dynamic international stock markets networks to detect the changes of linkage patterns under phases of financial turmoil and unconventional monetary policies (i.e., QE) implementations. We find evidence in our constructed static network, that the short-run error adjustment effects and the regional cointegration between emerging stock markets located in Asia-Pacific, Middle East, Africa and Latin America, have deepened since 2007. Further, most of the European stock markets formed a community and particularly, the stock markets of the "PIIGS" countries clustered significantly. Then, our investigated dynamic evolution networks demonstrate that short-run error adjustment effects and long-run equilibrium amongst the 46 stock markets have changed considerably over time. Our investigated time-varying network metrics combined could serve as a useful risk indicator to reflect both financial tranquil and turmoil phases over 2007–17. Ultimately, in the case studies of the US, UK, Japanese, and "PIIGS" countries' stock markets, by comparing the QE activities implemented by the central banks of the Fed, BoE, BoJ, and the ECB, differences and/or similarities in the short-run error correction effects and long-run cointegration amongst the global stock markets could be found significantly under study.

4.1 Introduction

Since financial crises could lead to dramatic changes in investment behaviors, market fundamental and economic policies worldwide, it is important to study the short-run and long-run interdependency patterns between stock markets throughout periods of financial turmoil. Moreover, in the wake of the US Great Recession of 2007–09 and the outbreak of the following crisis in the Euro-Area, the US Federal Reserve (Fed), along with the Bank of England (BoE), Bank of Japan (BoJ) and European Central Bank (ECB) respectively announced and implemented a series unconventional monetary policies (UMP), which are commonly known as Quantitative Easing (QE) programmes to bolster weak asset markets, as well as to stimulate the real economy [20]. A general feature of the existing literature has been verified that episodes relating unconventional monetary policies could have influenced in the stock markets to some extent [21–23]. Yet such studies provide few insights about the effects of the occurrence of QE activity and the intensity of that activity on the patterns of linkages amongst stock markets in the context of the fiscal policy shock. Therefore, in this chapter, we aim to answer the questions that whether the recent financial crises and subsequent QE programmes conducted by the central banks of the Fed, BoE, BoJ, and the ECB have impacts on the time-varying interdependencies pattern between the corresponding US, UK, Japan, and Eurozone stock markets and other stock markets worldwide. Furthermore, we seek to consider the possibility that the differences and/or similarities in the short-run adjustment velocity towards the long-run equilibrium trend between stock markets during the financial turmoils, and phases of QE with econometric and network approach from time-varying perspective. This will enable us to see of the financial crises and QE have common effects on, or whether each phase had distinct effects.

Our primary emphases on this chapter is to adopt and develop the cointegration and ECM models to build up corresponding international stock markets networks to empirically study both time-varying short-run error correction effects, as well as long-run equilibrium relationships amongst global stock markets from 2007 to 2017. Moreover, with the purpose in mind, we tend to provide a better understanding the topological characteristics and evolution of such networks through the different phases of financial turmoil and the QE announcements and implementations in the aftermath of 2007–09 global financial crisis and European debt crisis. Specifically, our empirical analysis is structured as follows: Initially, we conduct the cointegration models to estimate each pair of stock market indices from 46 countries/regions to confirm whether exist common stochastic trend driving pairwise national stock markets co-movement. In the following, the ECM models are employed to assess the short-run error self-adjustment effects and further validate the long-run equilibrium among the stock markets. Subsequently, our innovation is to study the complex behaviors among 46 stock markets through the constructed static and dynamic networks of the international stock markets based on the estimated results from ECM models. In particular, the network metrics, namely, average network strength and network degree, network density, clustering coefficient, reciprocity, and average path length are used to capture the time-varying network topological features of the international stock markets throughout the sample period. Finally, our study gives insight into how recent financial crises and QE activities could affect the interactions of international stock markets, by quantitatively exploring the potential differences and/or similarities in dynamic equilibrium self-adjustment effects of stock markets in the US, UK, Japan, and "PIIGS" countries (i.e., Portugal, Italy, Ireland, Greece and Spain) over the period of 2007–17.

Our empirical results lead to interesting findings. First, the results of the static network analysis of the international stock markets demonstrate that the short-run deviation adjustment effects, as well as the regional cointegration between emerging stock markets, have deepened since the recent global financial crises started from 2007. Meanwhile, the static topological structure reveals that most of the stock markets from Europe formed a community, while their interdependencies become more heterogeneous. This may reflect the European sovereign-debt crisis, which affected some but not all European countries. Particularly, the "PIIGS" countries which include the stock markets of Portugal, Italy, Ireland, Greece and Spain clustered significantly. Second, modelling of the dynamic evolution networks reveal that the short-run error adjustment effects and long-run equilibrium amongst the 46 stock markets have changed considerably over time. The applied time-varying network metrics combined could serve as a useful risk indicator to reflect the effectiveness of different phases of financial tranquil and turmoil over 2007–17. Finally, the case studies of the US, UK, Japanese, and "PIIGS" countries' stock markets distinguish that the short-run error self-adjustment effects, as well as long-run equilibrium relationships is likely to vary across different markets under the impact of the financial turmoil and QE activities throughout the sample period from 2007 to 2017. Our results point out that both of the US and UK stock markets have the quickest error self-adjustment speed during the Lehman Brother collapse in September 2008 than that of the stock markets of Japan and "PIIGS" countries. While during the period of Northern Rock crisis in October 2007 and European sovereign debt crisis in August 2011, the UK stock market reacted swiftly to its short-run deviations for maintaining the long-run equilibrium than other stock markets of US, Japan and "PIIGS" countries. As related to the Japanese stock market, the presence of persistent and faster self-adjustment effects happened from January 2009 to January 2010, as well as associated with Great East Japan Earthquake in 2011. Comparatively, the five "PIIGS" stock markets show more significant short-run error correction effects than the US, UK and Japanese stock markets during the Greek sovereign debt crisis in 2010. In addition, by comparing the QE activities announced implemented by the Fed, BoE, BoJ, and the ECB, different error correction effects and long-run cointegration amongst the global stock markets could be found significantly under study.

The remainder of this chapter is structured as follows. Subsection 4.2 presents relevant literature on the topic. Subsequently, in Subsection 4.3, the methodologies to be adopted for networks construction are presented. As a preliminary analysis, Subsection

4.4 describes the data and the statistical analysis of each stock market. In Subsection 4.5 and Subsection 4.6 we present empirical results of the analysis of the static and dynamic network of the international stock market. Eventually, Subsection 4.7 states the conclusions.

4.2 Literature Review

The most common type of interactions in the financial market is the co-movements of the asset returns. [4] originally applied the Pearson's correlation coefficient as the similarity between asset returns to build up the corresponding financial networks. After this seminal work, the application of complex network theory has been becoming a leading tool for understanding complex economic and financial systems [6, 55, 88–90]. For instance, Kullmann et al. [91] and Gao et al. [87] applied delayed cross-correlation function and Kenett et al. [92] constructed the partial correlation networks to underlying the complex structure of the financial market. Meanwhile, relying on econometric measures to construct the financial networks using asset returns to understand the market structure and capture systemic risk is popular recently. Billio et al. [8] employed Granger-causality tests to build up a time-varying financial networks using monthly equity returns of banks, broker/dealers, insurance companies as well as hedge funds. Through computing network-based measures of connectedness, their results indicated that banks play a more important role in transferring shocks than other financial institutions. Similarly, Wang et al. [13] used the Granger-causality models to construct extreme risk spillover network to analyze the interconnectedness across financial institutions from 2006 to 2015. Their findings suggested that during 2007–09 Global Financial Crises and recent European sovereign debt crisis, the structure of networks exhibited distinctive topological features. Diebold and Yilmaz [9, 10] applied equity return volatility data to build financial networks based on VAR models. Once the network is constructed, measures of network centrality, such as total directional connectedness, are computed. It is noteworthy that only taking into account of instantaneously (short-run) effects among asset returns inherent in the complex financial system might miss long-run information occurring on a long time scale [46]. To contain the long-run information between historical prices of stock markets, Yang et al. [93] built the cointegration-based network of stock markets from 26 countries/regions to explore the evolution of the long-run integrations during 2007–09 Global Financial Crisis and European sovereign debt crisis via dividing the data sample into four periods.

Specifically, to investigate the mutual dependencies and the degree of integration of the financial market from the perspective of econometrical measures is based on the cointegration theory [14, 63]. If two stock market price indices are cointegrated, it means that the two markets share common stochastic trends and maintain an equilibrium steady state to move together in the long run. Numerous studies have investigated the level of integration between the world's stock markets based on the cointegration and

ECM models. For instance, Kasa [67] applied the multivariate cointegration techniques [32, 63] to assess the international integration of the stock markets in the US, Japan, UK, Germany and Canada. His results indicated that the presence of a single common stochastic trend driving these national stock markets co-movement in the long run. Arshanapalli and Doukas [61] studied the cointegration amongst the stock markets of the Germany, UK, France, Japan, and US over 1988–1990. They provided evidence of the existence of long-run equilibrium relationships between the US and Asian stock markets since the stock market crash in October 1987. Their results also showed that the Asian stock markets are less integrated with the Japanese stock market compared to the US market. Masih and Masih [39] confirmed the presence of unique cointegrating vector in the nine stock markets of the US, Japan, Germany, UK, Hong Kong, Taiwan, South Korea, Singapore and Australia. Chen et al. [17] suggested the existence of cointegration relationship amongst the stock markets of Argentina, Brazil, Chile, Colombia, Mexico and Venezuela in the Latin America to force these markets to co-movement in the long run. [48] emphasized on the ten stock markets in the Asian region (i.e., Japan, Mainland, China, Hong Kong, Taiwan, South Korea, Singapore, Malaysia, Thailand, Indonesia and the Philippines), their results showed that the equity markets integration picked up in 2007–08.

On the other hand, the presence of cointegration implies that the dynamics of stock price changes can be described by an ECM model to capture the short-run error correction towards the long-run equilibrium [94]. In Masih and Masih [95]'s study, the cointegration relationships were found among stock markets of the US, Japan, Canada, France, Germany and UK pre- and post-1987 stock market crash. Through estimating the ECM models, their results showed that changes in the stock markets of Canada, UK and France to adjust to the mispricing of US stock market during the pre-crash period. However, over the post-crash era, the UK and German stock markets response much more significant to the US stock market equilibrium error. Mylonidis and Kollias [85] applied rolling cointegration and ECM models to reflect the dynamic process of convergence among four major European stock markets (i.e., Germany, France, Spain and Italy). According to the negative and statistical error correction coefficients, his study indicated that whenever the actual value of stock market prices for Germany and France fell short of equilibrium in a given period, the error correction mechanism helped bring them up to the long-run equilibrium value in the following period. Thus, the German and French stock markets seem to be more integrated and efficient markets, than the other two, in the sense that they return faster back to their equilibrium after a shock. Chien et al. [96] investigated the time-varying, long-run cointegration relationships between the China and ASEAN-5 stock markets, their results suggested that the estimated coefficients of error correction terms appear statistically significant and negative in China and Indonesia. Their findings suggested that whenever the actual values of these two stock prices fall short of equilibrium in a given period, the error-correction mechanism could cause them to swiftly adjust to maintain the long-run equilibrium value in the following period. Further, they explained such findings are caused by the fact that both China and Indonesia, the two largest economies among the six studied, are the major drivers of East Asian economic and financial integration. Singh et al. [97] investigated the long-run and short-run relations between the equity markets of the US and five BRIC countries (i.e., Brazil, Russia, India, and China). Through the ECM model, they found US equity market made adjustments in response to its deviations from the equilibrium, which acts as a restoring agent toward long-run equilibrium path in the event of any short-run departure. However, the Brazilian and Russian markets were following an independent dominant trend in the long run, which mean that they do not make a response to the lagged US stock market pricing errors.

Furthermore, in response to the great recession of 2007–09, the US Fed, BoE, BoJ as well as the ECB announced the large-scale asset purchases (LSAP) known as Quantitative Easing (QE) programs to recover the economies respectively [20, 98]. Bernanke and Kuttner's study indicates that monetary policy decision releases might produce a direct and immediate impact on financial markets [21]. For the individual market, Matsuki et al. [99] studied the Bank of Japan's current quantitative and qualitative easing (QQE) which introduced in April 2013 affects the Japanese economy by using a Markov-switching VAR model. Their results show that purchases of exchange-traded funds stimulate the stock and foreign exchange markets in Japan. For the cross-border markets, Tillmann [100] suggested that the US QEs has substantial effects on emerging market economies, especially on their capital inflows, equity prices, and exchange rates. Rai et al. [101] applied an event-study method to assess that emerging market economics response to the US Fed's tapering policy. Kryzanowski et al. Kryzanowski et al. [102] examine the correlations between bond markets, stock markets, and currency forwards during the QE programs launched by the US Fed. Rogers et al. showed the effects of unconventional monetary policy by the Federal Reserve, Bank of England, European Central Bank and Bank of Japan on bond yields, stock prices and exchange rates [103].

4.3 Network Representation of the International Stock Market

In ECM models, what we are most interested in is the respective error adjustment coefficients in ECM models. If the estimated δ between pairwise stock markets are significant as expected after the Statistically Validation Test described in Chapter 2, afterward, we build up the corresponding ECM-based international stock market network.

Let a graph $G(V, E, W)$ represents the directed and weighted ECM-based global stock market network, where V is the set of vertices which denotes the various stock markets, E is the edge set to represent the short-run error correction effects and long-run cointegration between each pair of vertices. W is the set of edge weights in which w is the weight of the connected edges between nodes v_i and v_j $(i, j = 1, 2, ..., n)$. Each network edge is assigned weight W, which is the error adjustment coefficients between pairwise stock markets. Specifically, if a market i reacts to restore disequilibrium to maintain the long-run equilibrium towards j, then a directed link is drawn from i to j. The adjacent matrix $\mathbf{W}$ of this international stock market network can be represented as follows

$$W_{i\to j} = \begin{cases} w_{ji}, & i \text{ responses to its short run deviations to restore cointegration with } j \\ 0, & \text{otherwise} \end{cases} \tag{4.1}$$

The magnitude of w_{ji}, namely, the error correction coefficients indicate the speed of deviations of stock i from long-run equilibrium will feed-back on the change in the i in order to force the movement towards the long-run equilibrium with j. It is worth noting that the significant short-run error adjustment effects between stock markets further confirm the existence of a cointegration relationship between pairwise stock markets.

4.4 Data and Descriptive Statistics

4.4.1 Data Description

In this study, instead of daily, we choose the weekly closing price for 46 countries/regions' stock market within the MSCI ACWI index[1], so that the adverse effects of belonging to different time zones and having different operating days are minimized. The data were obtained from DataStream, and the sample period used starts on 5 January 2007 and ends on 30 June 2017. The list of these 23 MSCI developed and 23 MSCI emerging stock markets are presented in Table. 4.1. All data are expressed in terms of US$ currency in order to have conformity and avoid the effects of local inflation and national currency fluctuation on the indices [104].

Since the 46 national stock market indices have different scales, they must be rescaled so as to be comparable. The first step is to calculate the percentage changes of each stock market index, which are given by

$$\Delta_i(t) = \frac{P_i(t)}{P_i(t-1)}, \text{ for all t} \geq 2, \tag{4.2}$$

where $P_i(t)$ is the price of index i in week t. For the rescaled index series $R_i(t)$, we set the first entry in each series to be $R_i(1) = 1$, and then $R_i(t)$ is expressed, for all subsequent entries in each series, by

$$R_i(t) = R_i(t-1) * \Delta_i(t), \text{ for all t} \geq 2. \tag{4.3}$$

[1]The MSCI ACWI Index (Morgan Stanley Capital Investment All Country World) captures large andmid cap representation across 23 Developed Markets and 23 Emerging Markets. With 2,497 constituents, the MSCI ACWI index covers approximately 85% of the global investable equity opportunity set.

After rescaling the original stock index series, we finally transform them into natural logarithms [2] for the cointegration and error-correction mechanism tests.

Table 4.1. List of the 46 countries/regions' stock market indices.

	Country/Region	**Symbol**	**Continent**		**Country/Region**	**Symbol**	**Continent**
	Developed Markets				**Emerging Markets**		
1	Canada (S&P/TSX)	CAN	Americas	24	Brazil (BOVESPA)	BRA	
2	United Stated (S&P500)	US		25	Chile (IPSA)	CHIL	
3	Austria (ATX)	AU		26	Colombia (IGBC)	COL	Latin
4	Belgium (BEL20)	BEL		27	Mexico (IPC)	MEX	Americas
5	Denmark (OMXC20)	DEN		28	Peru (IGBVL)	PER	
6	Finland (OMXH25)	FIN		29	Czech Republic (PX)	CR	
7	France (CAC40)	FRA		30	Egypt (EGX30)	EGY	
8	Germany (DAX30)	GER		31	Greece (ATHEX20)	GRE	
9	Ireland (ISEQ)	IRE		32	Hungary (BUX)	HUN	Europe,
10	Italy (FTSE MIB)	ITA	Europe,	33	Poland (WIG)	POL	Middle East,
11	Netherlands (AEX)	NET	Middle East	34	Qatar (DSM200)	QAT	Africa
12	Norway (OSLO)	NOR		35	Russia (RTS)	RUS	
13	Portugal (PSI20)	POR		36	South Africa (FTSE/JSE)	SA	
14	Spain (IBEX35)	SPA		37	Turkey (BIST)	TUR	
15	Sweden (OMXS30)	SWE		38	United Arab Emirates (ADX)	UAE	
16	Switzerland (SMI)	SWI		39	India (BSE100)	IND	
17	United Kingdom (FTSE100)	UK		40	Indonesia (IDX)	INDO	
18	Israel (TA125)	ISR		41	Korea (KOSPI)	KOR	
19	Australia (ASX)	AUS		42	Malaysia (FTSE BURSA)	MAL	Asia
20	Hong Kong (HSI)	HK	Asia-	43	Pakistan (KSE100)	PAK	
21	Japan (NIKKEI225)	JAP	Pacific	44	Philippines (PSEI)	PHI	
22	New Zealand (S&P/NZX 50)	NZ		45	Taiwan (TAIEX)	TW	
23	Singapore (ST)	SIN		46	Thailand (SET)	THA	

4.4.2 Descriptive Statistics

The detailed descriptive statistics of the 46 countries/regions' stock prices returns (after rescaled) covering the entire sample period from January 2007 to June 2017 are summarized in Table. 4.2. As displayed in Table. 4.2, the mean returns are lower in the developed markets, whereas relatively higher for emerging stock markets. In the emerging stock markets, the highest weekly mean returns are the market of Pakistan, followed by markets of the Thailand, Qatar, and Philippines, and the stock market of Greece has the lowest weekly mean returns. For the developed stock markets, the highest mean weekly returns appear in the market of Denmark, whereby the stock markets of Norway, Italy, and Portugal are found to have the relative lower mean returns compared to others. As anticipated, the emerging stock markets appear to exhibit higher volatility, as indicated by larger standard deviation values with the exception of stock markets of Malaysia (0.024). Especially, the stock market of Greece (0.053) and Brazil (0.053) has the most volatile price among countries included in this study, which indicate the high-risk property of them. For the developed markets, the standard deviations show that the

[2]The empirical analysis is based on a logarithm transformation of stock indices series to minimize the heteroscedasticity in the value of the level series.

stock market of Norway (0.020) has the lowest volatile, followed by the markets of US (0.026), Japan (0.027), Switzerland (0.028) as well as New Zealand (0.029) respectively. Conversely, volatility is the highest for the Austrian stock market (0.043), followed by the stock markets of Italy (0.042), Spain (0.041), thereby indicating that investment in these developed stock markets may prove to be riskier than in the other markets. The statistic value of skewness for each stock market returns is smaller than zero, which point to all stock market returns being skewed to the left. The value of kurtosis is greater than 3 for each index returns, which demonstrates leptokurtic distribution. Finally, the outcome of common patterns of non-Gaussian distribution is also validated with the Jarque-Bera (J-B) test since the test statistic rejects the null hypothesis of normality for each market return in each country/region.

Table 4.2. Descriptive Statistics of the weekly stock market indices returns of each country/region from January 2007 to June 2017.

Country/Region	**Mean**	**Max**	**Min**	**Std.dev**	**Skewness**	**Kurtosis**	**Jarque-Bera**
CAN	0.000177	0.164	-0.266	0.035	-1.313	12.902	2391.853∗
US	0.000990	0.114	-0.201	0.026	-0.967	11.805	1852.062∗
AUS	-0.000883	0.187	-0.363	0.043	-1.508	13.980	2954.966∗
BEL	-0.000502	0.102	-0.283	0.035	-1.543	12.528	2286.028∗
DEN	0.001234	0.132	-0.246	0.035	-1.460	11.230	1738.106∗
FIN	-0.000207	0.118	-0.202	0.036	-0.915	6.910	424.759∗
FRA	-0.000375	0.139	-0.273	0.037	-1.121	9.952	1216.116∗
GER	0.000905	0.145	-0.266	0.037	-1.057	9.954	1203.853∗
IRE	-0.000829	0.129	-0.339	0.038	-1.881	16.236	4315.562∗
ISR	0.000935	0.148	-0.174	0.032	-0.767	8.315	697.533∗
ITA	-0.001524	0.131	-0.266	0.042	-1.035	7.356	530.180∗
NETH	-0.000190	0.139	-0.310	0.036	-1.441	14.581	3246.327∗
NOR	-0.001334	0.086	-0.079	0.020	-0.104	4.608	59.911∗
POR	-0.001665	0.102	-0.228	0.036	-1.061	7.170	498.987∗
SPA	-0.000813	0.125	-0.260	0.041	-0.953	7.536	551.721∗
SWD	0.000264	0.162	-0.238	0.039	-0.715	8.074	633.287∗
SWI	0.000471	0.131	-0.243	0.028	-1.521	16.475	4349.265∗
UK	-0.000426	0.163	-0.278	0.032	-1.359	15.153	3534.532∗
AUST	0.000040	0.132	-0.355	0.039	-1.839	17.136	4862.505∗
HK	0.000440	0.119	-0.177	0.032	-0.269	5.870	194.281∗
JAP	0.000391	0.070	-0.220	0.027	-1.234	11.728	1875.265∗
NZ	0.000347	0.103	-0.237	0.029	-1.613	13.191	2603.984∗
SIN	0.000212	0.178	-0.208	0.030	-0.488	11.137	1530.757∗
BRA	-0.000062	0.257	-0.331	0.053	-0.516	8.478	708.296∗
CHI	0.000640	0.171	-0.333	0.035	-1.727	18.863	6007.053∗
COL	-0.000554	0.124	-0.273	0.038	-1.185	9.532	1100.346∗
MEX	0.000259	0.239	-0.302	0.042	-0.598	12.454	2069.733∗
PER	0.000414	0.187	-0.371	0.041	-1.351	17.683	5079.959∗
CR	-0.001030	0.189	-0.328	0.040	-1.237	13.838	2816.421∗
EGY	-0.000952	0.147	-0.453	0.047	-2.503	21.597	8453.864∗
GRE	-0.003367	0.171	-0.258	0.053	-0.564	4.831	105.404∗
HUN	0.000091	0.202	-0.353	0.048	-0.966	10.586	1396.619∗
POL	-0.000023	0.249	-0.290	0.045	-0.883	10.967	1517.944∗
QAT	0.001725	0.149	-0.231	0.033	-1.351	12.245	2114.272∗
RUS	-0.001193	0.342	-0.237	0.051	-0.152	9.202	878.697∗
SA	0.000295	0.242	-0.201	0.042	-0.077	7.722	508.662∗
TUR	0.000119	0.246	-0.285	0.052	-0.450	6.632	319.095∗
UAE	0.000640	0.110	-0.185	0.028	-1.011	9.538	1067.551∗
IND	0.000924	0.199	-0.214	0.039	-0.287	6.403	271.416∗
INDO	0.001402	0.175	-0.277	0.038	-0.926	11.150	1591.863∗
KOR	0.000631	0.265	-0.288	0.040	-0.701	13.389	2504.469∗
MAL	0.000463	0.113	-0.101	0.024	-0.401	5.509	158.141∗
PAK	0.001795	0.095	-0.210	0.031	-1.472	9.904	1283.906∗
PHI	0.001700	0.127	-0.214	0.033	-0.870	8.151	673.672∗
TW	0.000643	0.096	-0.122	0.030	-0.630	4.728	104.244∗
THA	0.001785	0.111	-0.272	0.031	-1.279	13.744	2780.260∗

Notes: ∗ indicates rejection of the null hypothesis at the 1% significance level.

4.5 Static Network Analysis of the International Stock Market

Since cointegration requires the variables to be integrated of the same order, i.e., $I(1)$, hence we initially examine the 46 stock market price indices for unit roots to verify their stationarity. This is done by way of the ADF and PP unit root tests on the levels and first differences of each stock market index for the stationarity test. The estimation results reported in Table B.1 suggest that the null hypothesis of a unit root test is not rejected at 1% significance level by both ADF and PP tests for any stock market indices in the log levels. While the first differences series reject the null hypothesis, indicating that they are $I(1)$ series. Given the fact that the two series exhibit the same order of integration, we also examine the possibility of a long-run equilibrium relationship linking them in log level, and only stationary regression residuals indicating cointegration existed. For sake of space, here we do not present the results of stationarity tests for the estimated residuals from cointegration equations. Once the cointegration relationships determined, we proceed to conduct the ECM models for each pair of countries' stock market indices. Then we adopt the BH proceed (with FDR $\alpha = 0.01$) to confirm the statistical significance level for the estimated error correction coefficients from ECM models. Consequently, the presence of all the negative and statistically significance error correction coefficients between pairwise stock market indices further establish the static network of 46 national stock markets throughout the sample period, from 5 January 2007 to 30 June 2017.

Fig. 4.1illustrates how the network interconnectedness and fragmentation amongst 46 national stock markets throughout the sample period 2007–17. Visually, we can see how the state of the international stock markets is reflected in the topology of the underlying network based on ECM models. Here, the visualization of the ECM-based static financial network is using ForceAtlas2 algorithm [105], which divided each network element into different groups naturally. The vertices are colored according to geographical locations, orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa. As depicted in Fig. 4.1, the outgoing degree of each stock market reflects that it reacts to its short-run departures and to return to the equilibrium state with other stock markets. Therefore, the greater the outgoing degree, highlighting the corrective stance of the stock market in the system to restore the long-run equilibrium. Contrasting to that, the greater incoming degree of one stock market indicates that its last-period's change made other stock markets act as a restoring agent towards their short-run departures to maintain the long-run equilibrium. The economic logic behind it that appeals to common sense, the deviations may persist in the short run between stock markets, but there would be a tendency for the system to move back to the equilibrium state in the long run. Thus, the existing of the directional error adjustment effects between stock markets could further confirm the existing of a common stochastic trend to drive them in the long-run equilibrium state, i.e., cointegration relations.

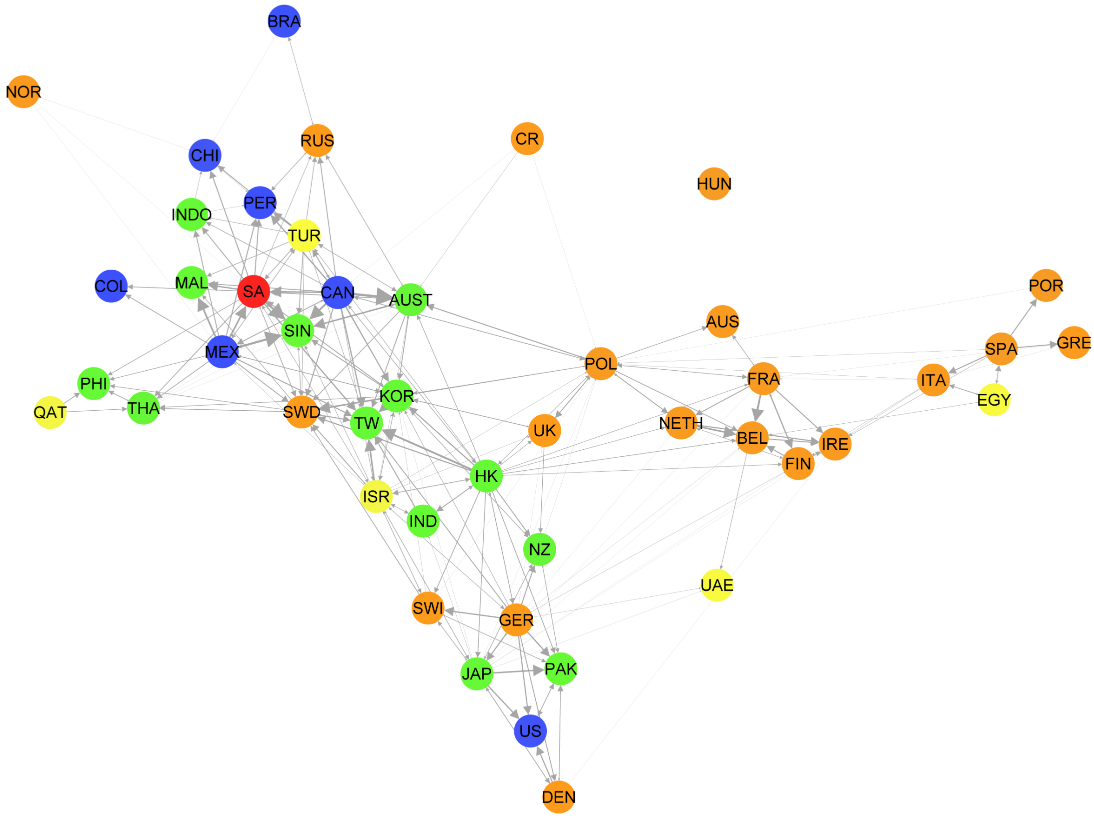
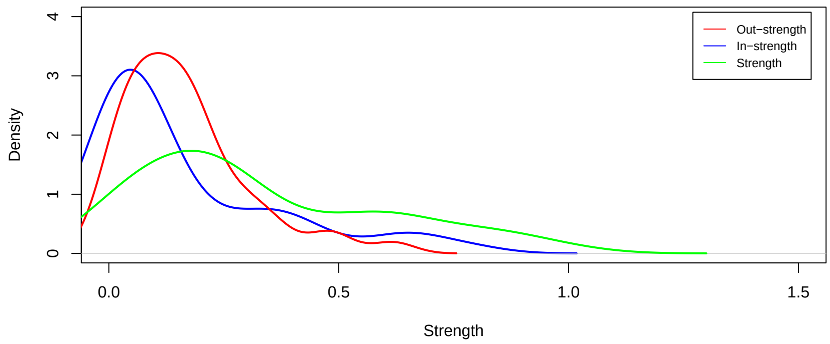


Fig. 4.1. The static network of 46 national stock markets from January 2007 to June 2017. The countries/regions are color-coded according to their geographical locations: orange for Europe, blue for the Americas, green for Asia-Pacific, yellow for the Middle East, and red for Africa.

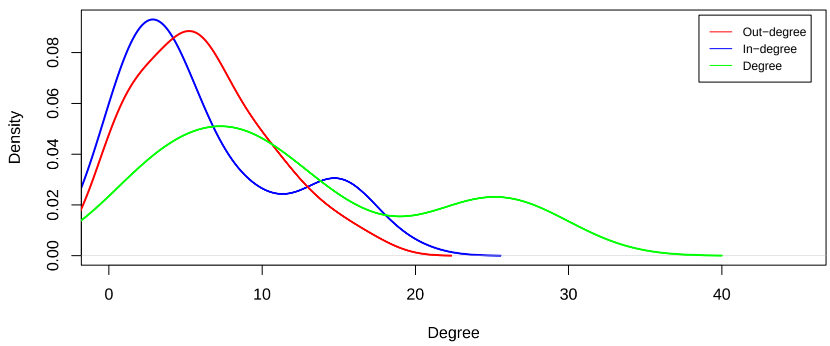
More specifically, graphical observations from Fig. 4.1 indicate that the 46 stock markets investigated under study can be classified by the continents naturally. The emerging stock markets, which from Asia-Pacific, Middle East, Latin America and Africa have faster short-run error adjustment effects, and they are long-run cointegrated much more significantly with each other over 2007–17. The majority of the stock markets of the European countries, closely connected and clustered as a community individually. Interestingly, in this community, where we identify the troubled "PIIGS" countries, stock markets in the Portugal, Italy, Ireland, Greece and the Spain strongly linked and formed their own cluster. While the European stock markets of the UK, Poland, Austria, Netherlands, Belgium, Finland, Ireland, and France constructed as another small cluster. In particular, the stock markets of Poland and UK, serving as bridging countries that connect the European and Asian-Pacific stock markets. By contrast, the rest of the European stock markets, namely, the stock market of Norway, Russia, Sweden, Switzerland, Denmark as well as Germany have more integrations with other regional stock markets than the local European markets. As for the Asia-Pacific region, the stock markets of Hong Kong, Australia, New Zealand and Pakistan, acting as a bridge to link the European and regional stock markets. Most evidently, one can note that the stock markets of the Japan, German, Pakistan, and Denmark are closely connected to US stock market, which demonstrates that there exist stronger short-run error adjustment effects as well as long-run equilibrium relationships with each other. As illustrated in Fig. 4.1, the Latin American cluster formed and contains the major stock markets in Chile, Brazil, Colombia, Mexico, Peru. Further, we find that there is no significant evidence of the existence short-run error correction effects and long-run cointegration among the US-BRICS markets (i.e., stock markets of Brazil, Russia, India and South Africa).

Overall, based on our constructed static network of international stock markets, which individual stock market responds to disequilibrium and to maintain the long-run equilibrium with other markets could be observed clearly. The economic intuition behind is that when there exists a short-run deviation from the equilibrium cointegrating relationship as measured by the error correction coefficients in ECM models, it mainly happened in the emerging stock markets. Especially, the Asian, Latin American and South African stock markets tend to adjust to clear the disequilibrium and bear the brunt of short-run adjustment to re-establish the long-run equilibrium relationship with each other throughout the sample period of 2007–17. Further, Fig. 4.1 demonstrates that the European markets are loosely connected with each other, and connections becomes heterogeneous amongst the stock markets of Norway, Russia, Sweden, Switzerland, Germany, Denmark and the rest of the European market. This may reflect that the European sovereign debt crisis, which affected some but not all European countries. Besides, the statistically significant short-run error adjustment effects between stock markets which appear to explain the cointegration in prices, suggesting that the potential for diversifying risk by investing in different stock markets of Latin America, Asian-Pacific as well as "PIIGS" countries are limited, respectively. These results are critically important for long-run investors in their act of portfolio and risk management. Specifically, from the diversification view, strong long-run cointegration among Asian and Latin American stock markets implies that investors may face similar risk exposures in the underlying markets over time, and thus should be indifferent to investment choices [96]. Likewise, our results show a high level of cointegration across the European stock market, these findings suggest that absence of potential benefit diversification across these markets. While, a low level of cointegration is noted among European-Asian, and European-Latin American markets, which highlights the benefits of diversification.

Moreover, to deep understanding the topological features of the static network of international stock markets from January 2007 to June 2017, the distributions of the in- and out-strength, in- and out-degree, as well as the total-strength and total-degree of this network, are presented in Fig. 4.2 via the Probability Density Functions (hereafter referred to as PDF). The results indicate that all the error correction coefficients have the expected sign (presented as the absolute value in Fig. 4.2(a)) and lie between the usual range of 0 and 1 in our static network of international stock markets covering the entire period from 2007 to 2017. From Fig. 4.2, one can see that the total- and in-strength, total- and in-degree distribution of the international stock markets network exhibit longer fat tails, respectively. Specifically, the fat-tail phenomena are visible from the total-strength and total-degree distributions mean that most stock markets in the network are lowly linked and only a small part of stock markets are highly linked and associated with quicker disequilibrium adjustment speed. Furthermore, both in- and out-strength of the global stock markets network also highlight the fat-tailed distributions, which points to the existence of a small part of stock markets exert faster error correction speeds in the system, whilst the majority stock markets exhibit a greater uniformity and response relatively slower.



(a) Strength distribution of world stock market network



(b) Degree distribution of world stock market network

Fig. 4.2. The strength and degree distribution of the static network of the international stock markets over 5 January 2007–30 June 2017.

4.6 Dynamic Network Analysis of the International Stock Market

Turning to the dynamic network analysis, in order to explore the topological characteristics of the time evolution of ECM-based networks of the international stock markets over time, the network metrics are used as the indicators of the systemic risk in the dynamic networks. Specifically, to capture this fact, our methodology builds on the framework of sliding window technique with a rolling window length of ΔT =48 consecutive trading weeks (i.e., one calendar year). In each time window, we construct a corresponding stock market network of 46 countries/regions, then calculate and display the time-varying network metrics to quantify its stability and structure on system-level in Section 4.6.1. In the following, we statistically identify the potential differences and/or similarities in the dynamic error adjustment effects of the stock markets in the US, UK, Japan, and the "PIIGS" countries during the different phases of financial turmoil and QE activities in Section 4.6.2.

4.6.1 System–level Analysis

We summarize the evolutionary results through the time of six important metrics of our constructed dynamic networks of the international stock markets over 2007–17 in Figs. 4.3–4.8. The general observational findings are that the time-varying network statistics could reflect the dynamic changes of the world stock market to different extents. Particularly, our investigated network metrics combined can serve as a good risk indicator to reflect both tranquil and turmoil periods of the global financial markets over the entire sample period from January 2007 to June 2017. In addition, one should be aware that from Fig. 4.3 to Fig. 4.8, the points in the horizontal axis are the start time points of the rolling windows.

Dynamic Average Network Strength

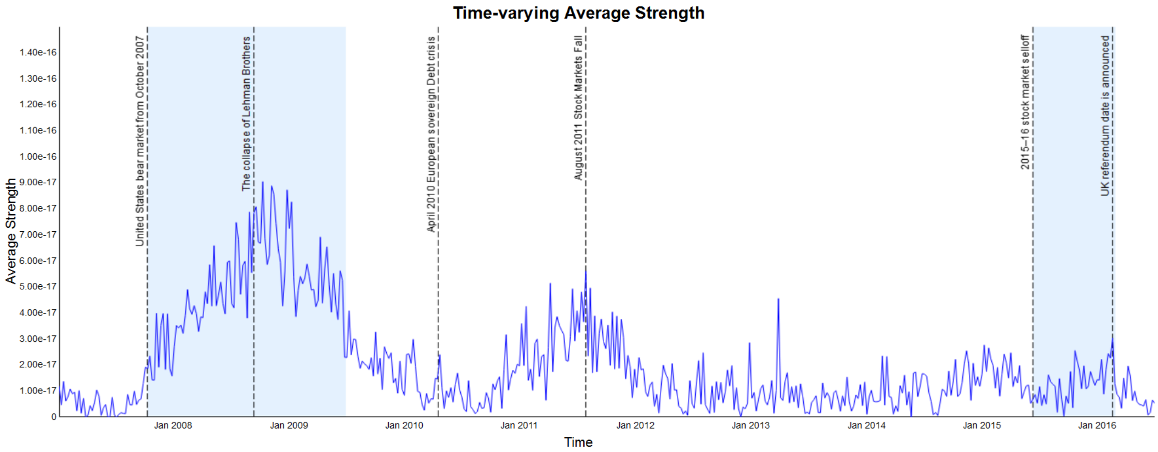


Fig. 4.3. Average network strength of the international stock market as a function of time. The first blue region represents the US bear market of 2007–09 (from 11 Oct 2007 to June 2009), and the second blue region denotes the 2015–16 stock market sell-off. The vertical dashed lines correspond the date of the crises.

Dynamic Average Network Degree

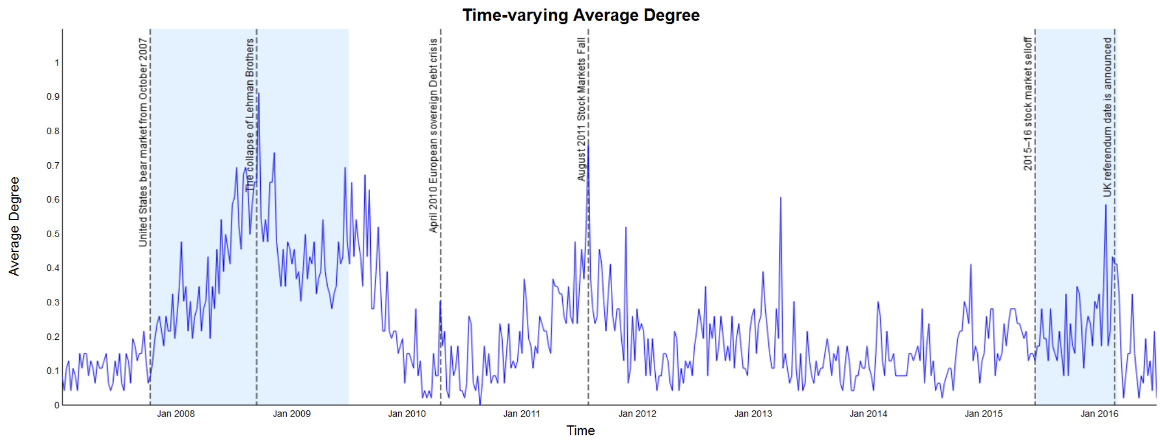


Fig. 4.4. Average network degree of the international stock market as a function of time. The first blue region represents the US bear market of 2007–09 (from 11 Oct 2007 to June 2009), and the second blue region denotes the 2015–16 stock market sell-off. The vertical dashed lines correspond the date of the crises.

In Fig. 4.3, the time-varying average network strength (i.e., the average speed of short-run error correction values) of the international stock markets reveals that the short-run departures from long-run equilibrium were typically corrected among the 46 national stock markets. Once there exhibits statistically significant error adjustment coefficients between pairwise stock markets, then they are necessarily cointegrated with each other. Therefore, the dynamic average degree (see Fig. 4.4) of the international stock markets network can be viewed as the variation of market long-run cointegration amongst 46 national stock markets. At first glance, in Fig. 4.3 and Fig. 4.4, we find that the dynamic average network strength and degree of the global stock markets both fluctuate over time, and there were a clear upward movements during periods of financial turbulence and followed gradual drop after the turmoil. Specifically, there has been a substantial increase from October 2007 until August 2008, and rose steeply after the Lehman Brother collapse on 15 September 2008. Then these two network metrics decreased gradually until started increasing again during the middle of 2009 associated with the announcement of the Great Recession officially ended. It is noteworthy that the average network strength and degree increase up correspond to the sovereign debt crisis in Europe (i.e., during April 2010 and August 2011), and associated with financial uncertainty since Standard and Poors (S&P) announced that America's credit rating would be downgraded from AAA to AA+ 5th August 2011. In particular, in the case of 2007–09 Global Financial Crisis, these two network statistics climbed up to a higher position in comparison with the 2011 European sovereign debt crisis, indicating a stronger short-run error adjustment effects as well as long-run cointegration relations among stock markets indices worldwide. Finally, there are observable evident fluctuation for these two network metrics correspond to the period of the "2015–16 stock market sell-off", and rose steeply during January–February 2016. These phenomenon can be regarded as the evidence that the crude oil falling caused US stock market fell significantly, and the announcement of the "UK Referendum of Leaving EU" on 20 February 2016 caused the international stock markets changed evidently.

Dynamic Network Density

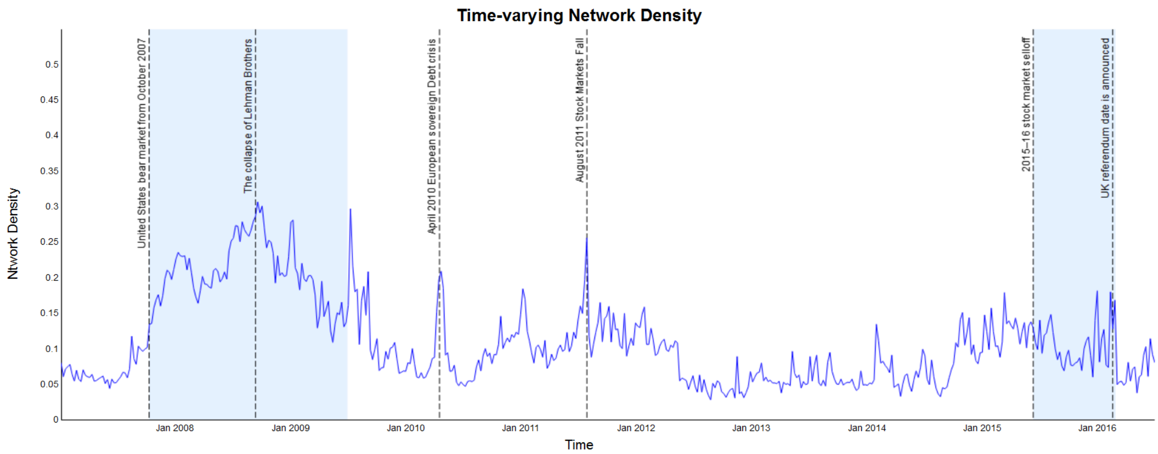


Fig. 4.5. Network density of the international stock market as a function of time. The first blue region represents the US bear market of 2007–09 (from 11 Oct 2007 to June 2009), and the second blue region denotes the 2015–16 stock market sell-off. The vertical dashed lines correspond the date of the crises.

Dynamic Clustering Coefficient

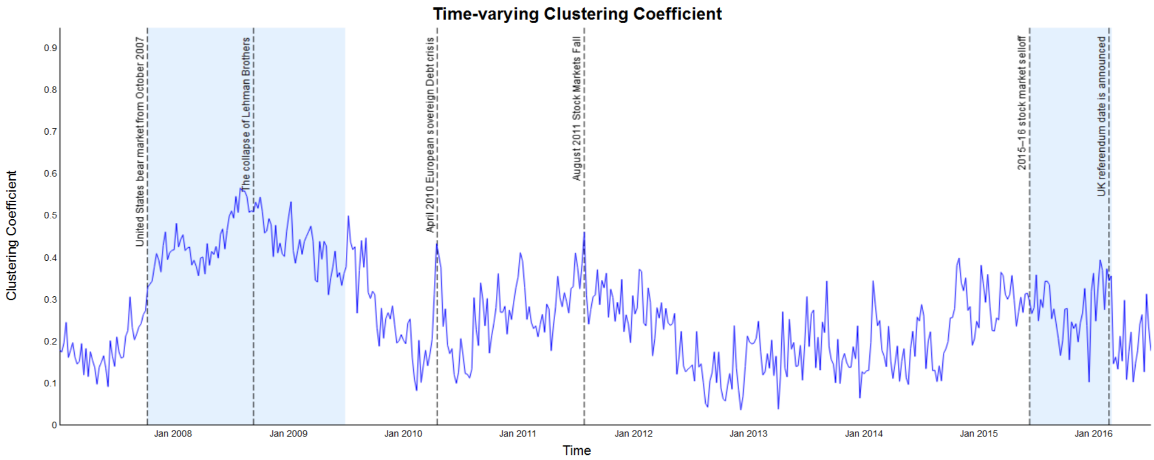
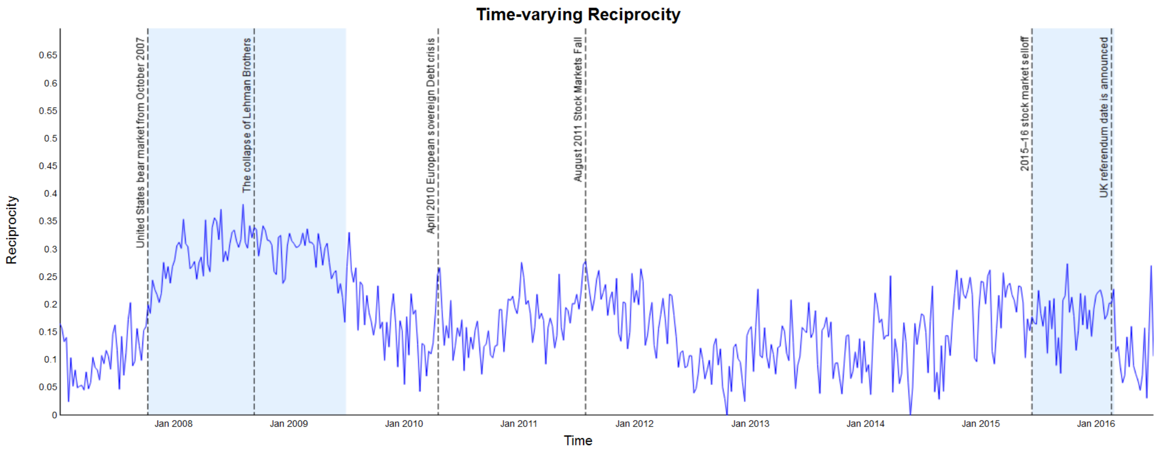


Fig. 4.6. Clustering coefficient of the international stock market as a function of time. The first blue region represents the US bear market of 2007–09 (from 11 Oct 2007 to June 2009), and the second blue region denotes the 2015–16 stock market sell-off. The vertical dashed lines correspond the date of the crises.

Dynamic Reciprocity



(a)

Fig. 4.7. Reciprocity of the international stock market as a function of time. The first blue region represents the US bear market of 2007–09 (from 11 Oct 2007 to June 2009), and the second blue region denotes the 2015–16 stock market sell-off. The vertical dashed lines correspond the date of the crises.

Dynamic Average Path Length

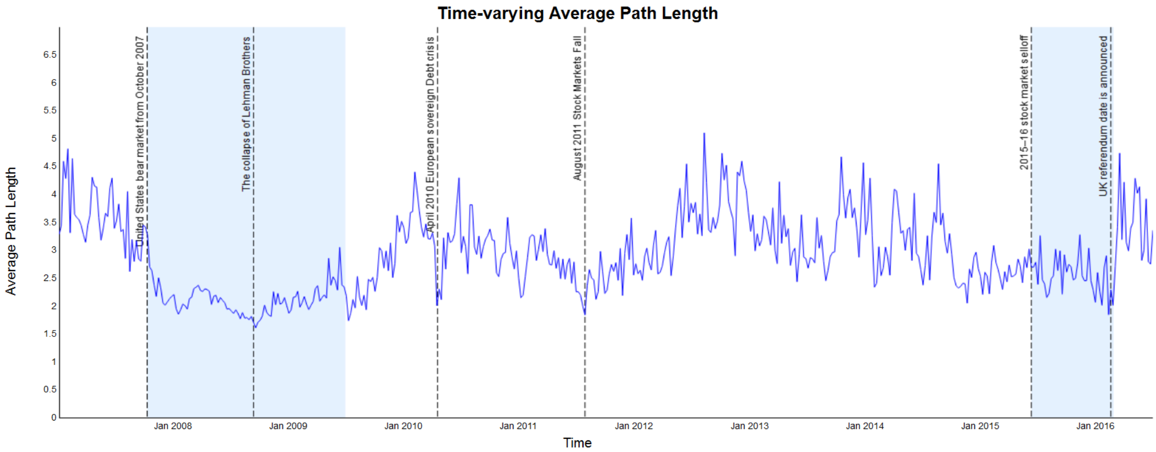


Fig. 4.8. Average path length of the international stock market as a function of time. The first blue region represents the US bear market of 2007–09 (from 11 Oct 2007 to June 2009), and the second blue region denotes the 2015–16 stock market sell-off. The vertical dashed lines correspond the date of the crises.

Interestingly, similar findings can be observed through the network metrics of dynamic network density in Fig. 4.5, dynamic clustering coefficient in Fig. 4.6 and the reciprocity in Fig. 4.7. Higher values of these network statistics suggest that the international stock markets is more clustered and compact throughout the phases of financial turmoil. However, the average path length of the international stock markets reflects the opposite results in Fig. 4.8, since the more connections in the network, the shorter the average path length. In summary, putting the observation from Figs. 4.5–4.8 together, presents that during the periods financial turbulence, the values of each network metric are higher (while lowest for time-varying average path length) compared to that in the other time windows during the normal periods. All the network metrics combined to highlight the structural change occurred in October 2007, and the highest (lowest for average path length) value appears during the global financial crisis in 2008 after the collapse of Lehman Brother on 15 September. In the following year, the dynamic networks of the international stock markets experienced another peak at June 2009, this situation might be caused by the announcement of the Great Recession officially ending in June 2009. The network metrics saw another dramatically structural change occurred correspond to the April 2010 Greek and August 2011 Euro-zone sovereign debt crisis. Further, the network metrics remain persistently stable from the mid-2012 until experience a steep increase in February and October 2014. Then the slight fluctuation occurred from Spring to August 2015 could be explained by the shock in Chinese stock market as well as a steep sell-off of the US stock market. Finally, we find that the dynamic network statistics of the global stock markets rose notably during January–February 2016. This might be attributed to the fact, that owing to the crude oil falling caused US stock market fell significantly and the UK referendum date was announced on 22 February 2016.

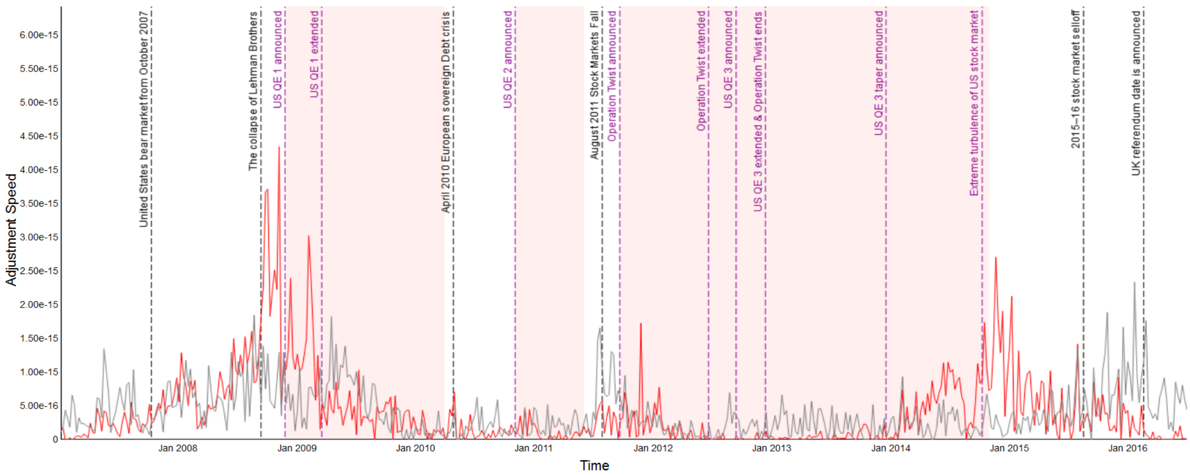
4.6.2 Cross-Market Short-run Adjustment Effect

To characterize the short-run error adjustment processes along a wide range of different stock markets, we conduct a dynamic network statistics analysis and account for their differences and/or similarities throughout the recent financial crises and the subsequent phases of QE implementation by Fed, BoE, BoJ, and ECB. Specifically, to achieve this objective, we display the both total out- and in-incoming strength, total out- and in-degree of the stock markets in the US, UK, Japan, and "PIIGS" countries (i.e., Portugal, Italy, Ireland, Greece and Spain) from the time-varying perspective respectively. Consequently, we could clearly observe the self-stabilization feedback effects that show how much of the short-run departures are being corrected for the respective stock markets to maintain the long-run equilibrium, especially throughout the phases of crises and specific occurrence or intensity of QE activity during the sample period.

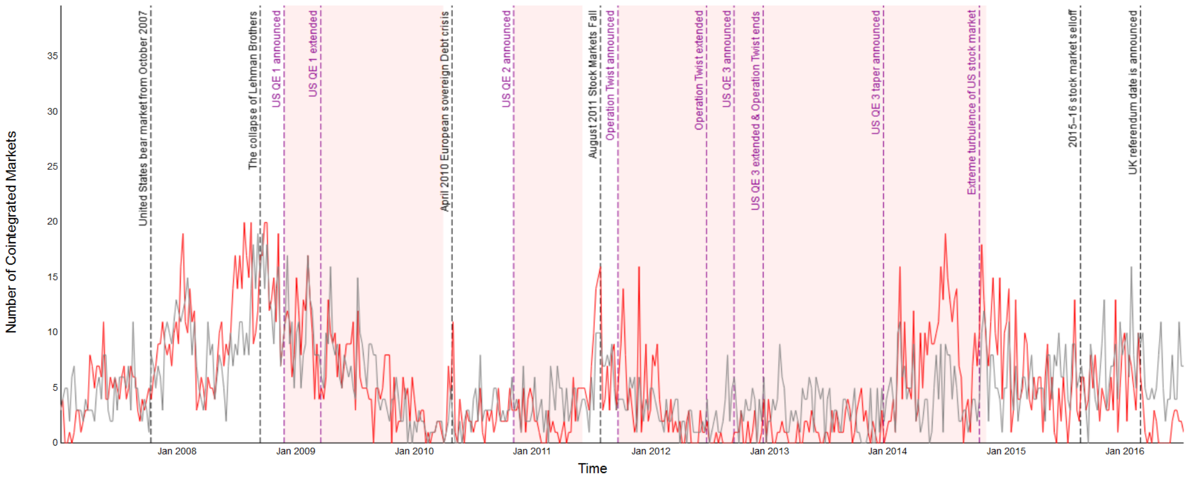
Case Study of US Stock Market

In the case of the US, a series of unconventional monetary policies put forward by the US Fed included the large-scale asset purchase programmes (LSAP), i.e., QE1, QE2, QE3, as well as the maturity extension programme, i.e., Operation Twist (OT) since 2008 [20, 106, 107]. The recent financial crisis, led ultimately the US Fed to launch the QE1 during December 2008–March 2010 (the first red region in the Fig. 4.9) after the collapse of Lehman Brothers in September 2008; QE2 took place between November 2010 and June 2011 (the second red region in the Fig. 4.9), and QE3 started in September 2012 and ended in late 2014 (the third red region in the Fig. 4.9). Besides, the OT conducted in September 2011, and the QE3 tapering programme launched in December 2013 (the third red region in the Fig. 4.9). Specifically, to study the effects of the occurrence and/or intensive of the QE activities on the interdependencies between the US stock market and other 45 international stock markets, the time-varying total out- and in-strength, total out- and in-degree of the S&P 500 index are presented in Fig. 4.9(a) and Fig. 4.9(b) respectively.

It should be noted that, the total out-strength of the US stock market (as presented with red line in Fig. 4.9(a)) reflects that, when the US stock market tends to short-run departures from the long-run equilibrium values with other 45 stock markets, which will in turn call for its adjustment in subsequent periods to maintain the equilibrium state with other national stock markets. While the opposite situation measured by the total in-strength of the US stock market in Fig. 4.9(a) with the gray line, which measures the short-run error adjustment speed at which other 45 stock markets return to long-run equilibrium after a last-period's change in the US stock market. Specifically, as depicted in Fig. 4.9(a), where changes of the in-strength (with gray line) of the US stock market during February, May, and August of 2007 can be seen clearly. These estimated results reflect that the increasing short-run error adjustment speed respective to other 45 national stock markets before October 2007, indicating that they respond to their departures from long-run equilibrium path with the US market significantly. In the other words, they are related to the US market's previous period's change during the US sub-prime mortgage crisis in 2007 and in turn call for their correction to maintain long-run equilibrium with US stock market. In the following October 2007, namely, the start of the US bear market of 2007–09, the out-strength (with red line) of US stock market tends to rise notably. Especially, the peak appeared after the bankrupt of Lehman Brothers on September 2008, which points out that the US stock market has the quickest reaction to its disequilibrium and restored the long run equilibrium with other 45 stock markets. The economic intuition behinds these results suggest that all adjustments for the steady cointegration fall on the US stock market during the extremely period of financial turmoil after bankrupt of Lehman Brothers, which highlights the US stock market is a more efficient and integrated market compared to other 45 markets. A similar situation happened since the announcement and implementation of the US QE1 from December 2008 until the launch of the US Fed's QE1 extension in March 2009. Whilst there is visible evidence shows that the in-strength (with gray line) of the US stock market starts to rise after the US Fed announced to extend QE1. This indicates that more stock markets worldwide have a stronger significant response to their deviations from the long-run equilibrium with US stock market through such extension period until the end of QE1 in 2010. Further, it can be also seen that the in-strength (with gray line) of the US stock market has begun to rise again during August 2011, indicating that the short-run error adjustment rates became faster of other 45 markets to follow the path with US stock market, associating with the Euro-zone sovereign debt crisis, and the Standard and Poors (S&P) announced that America's credit rating would be downgraded from AAA to AA+. Then, the estimated out-strength (with red line) of the US stock market experienced rise since the OT announced in December 2011 until the extension of OT in the mid-2012. The reverse results begin from the announcement of US QE3, the in-strength of the US stock market is quite larger than that of the out-strength for the US market during the phases of the QE3 announcement and implementation. Conversely, in February and October of 2014 associated with the Fed QE3 were halted by the Fed, the out-strength of the US stock market appears to increase notably. Especially, the shaper rise of the out-strength for the US stock market along with the extreme turbulent episodes from the end of 2014. This also suggests the US stock market respond quickly to its short-run departures to restore the long-run equilibrium, meaning that the US stock market bears the brunt of short-run adjustments to bring about the long-run equilibrium with other 45 national stock markets. Ultimately, our results reveal that the in-strength of the US stock market tends to rise notably during the 2015-16 financial turbulence, indicating that the disequilibrium is being corrected by other 45 national stock markets to maintain the equilibrium steady state from August 2015 until June 2016.



(a) Total out-strength (red line) and in-strength (gray line) of the US stock market



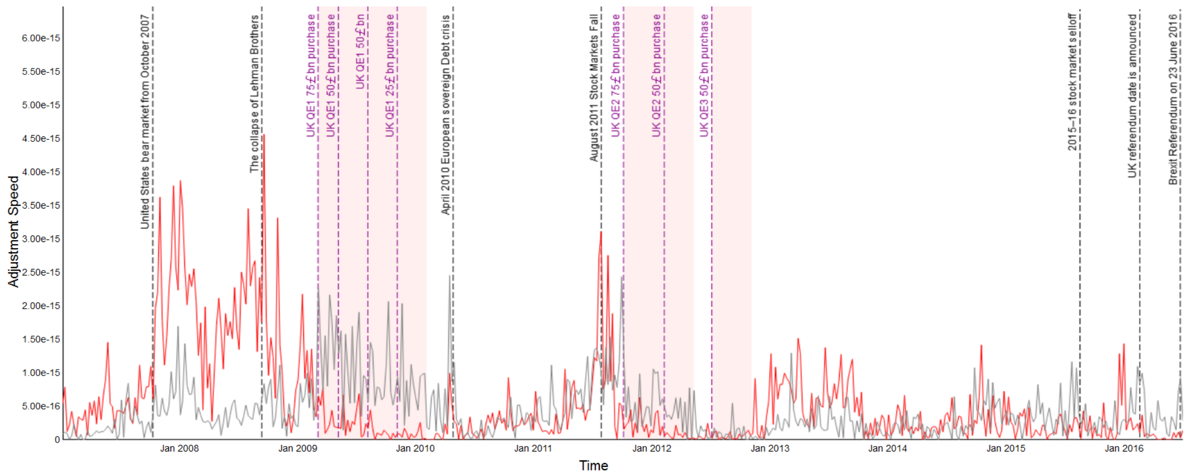
(b) Total out-degree (red line) and in-degree (gray line) of the US stock market

Fig. 4.9. Dynamic short-run error adjustment effects and long-run equilibrium relationships between the US and other 45 national stock markets. The red regions depict the corresponding duration of QEs in the US. The purple vertical dashed lines represent the announcement, extension and end dates of corresponding US QEs. The black vertical dashed lines show the dates of the financial turmoils.

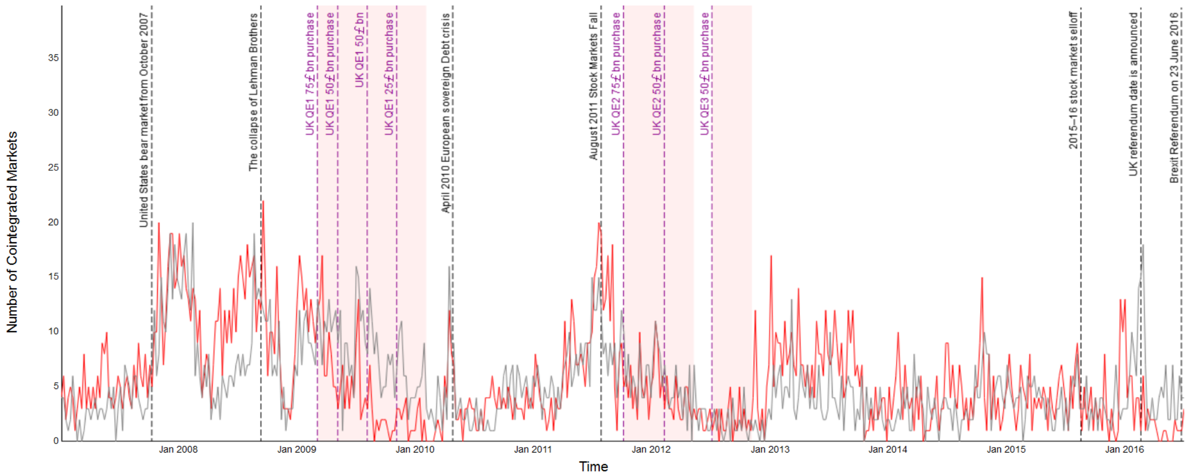
Overall, the US stock market has stronger short-run self-stabilization mechanism during most of the periods. Especially, it is worth noting that, disequilibrium in US stock market quickly respond and return to long-run equilibrium with other 45 stock markets during the most serious period of 2007–09 Global Financial Crisis (i.e., after the Lehman Brothers collapse), the periods that Fed's purchases were halted in October 2014, as well as the extreme turbulence in the US since the end of 2014. These observations are consistent with finding in [85], that the larger in magnitude speed of adjustment coefficients, the US stock market is expected to be more integrated, liquid and efficient market than other stock markets. On the other hand, the presence of the significant error correction coefficients in ECM models (the out- and in-strength of the US stock market in Fig. 4.9(a)) further confirm the presence of the steady long-run cointegral relationships. As displayed in Fig. 4.9(b), the varied number of cointegration relations between the US and other 45 national stock market from dynamic perspective can be observed through the out- and in-degree of the US stock market. In other words, the results imply that there is a common stochastic trend that lies behind the long-run co-movement between the US and other 45 stock markets worldwide. In line with the results observed in Fig. 4.9(a), the US stock market has higher out-degree (with red line) than in-degree (with gray line) during phases of financial turmoil through 2007 to 2017. This result further supports there exist quickly error adjustment for the cointegrations fall on the US stock market, especially, the increasing number of out-degrees during phases of financial uncertainty could be found and gradually declined after the turmoils in Fig. 4.9(b). Moreover, the interesting findings in terms of the effects of the Fed's QE on the cointegration between the US and other 45 national stock market, there are notably higher number of out-degrees of the US stock markets during the announcement and implementation of the QE1 and OT, as well as after the phases of the Fed launched the QE3 tapering in December 2013. In sum, the results indicate that cointegration relations between the US stock market and other 45 markets do not hold over the full sample, however, the evidence of cointegration over the phases of the recent financial turmoil and Fed's QE, indicating that the effects of financial uncertainty affecting the long-run equilibrium relationships vanish at a very slow rate.

Case Study of UK Stock Market

We next turn to the UK stock market, the time-varying total out- and in-strength, total out- and in-degree of the FTSE 100 index are depicted in Fig. 4.10(a) and Fig. 4.10(b). Importantly, different from the US Fed's QE policies, the UK BoE had purchased the total amount of £375 billion in assets, most of which was used to buy British government securities [20, 108**?** , 109]. Specifically, over the period March 2009 to January 2010, the BoE purchased total £200 billion of assets which overwhelmingly made up of government securities (i.e., QE1, as presented by the first red region in the Fig. 4.10). Then, between October 2011 and May 2012, the BoE bought an additional £125 billion of gilts (i.e., QE2, as presented by the second red region in the Fig. 4.10). Following a brief pause in purchases, in July 2012 the Monetary Policy Committee (MPC) launched a further £50 billion of gilt purchases and to be completed by November 2012 (i.e., QE3, as presented by the third red region in the Fig. 4.10).



(a) Total out-strength (red line) and in-strength (gray line) of the UK stock market



(b) Total out-degree (red line) and in-degree (gray line) of the UK stock market

Fig. 4.10. Dynamic short-run error adjustment effects and long-run equilibrium relationships between the UK and other 45 national stock markets. The red regions depict corresponding duration of QEs in the UK. The purple vertical dashed lines represent the announcement, extension and end dates of corresponding BOE QEs. The black vertical dashed lines show the dates of the financial turmoils.

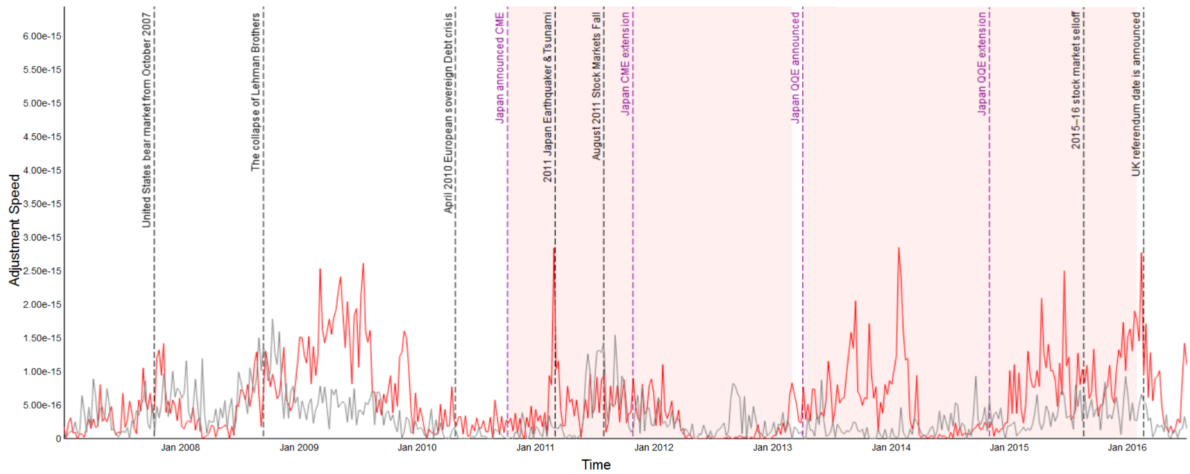
As depicted in Fig. 4.10(a), the evolutionary results suggest that the total out-strength (with red line) of the UK stock market gradually rose from January 2007 to October 2008. In particular, there are two steeply peaks along with the Northern Rock crisis in the UK and the start of the US 2007–09 bear market in October 2007, the other one is associated with the collapse of Lehman Brothers in September 2008. These results future support that the UK stock market has a quicker error self-adjustment effect and converged more rapidly towards full-equilibrium with other 45 stock markets. Conversely, through the entire announcement and implementation phases of the UK QE1 (March 2009–January 2010), QE2 (October 2011–May 2012) and QE3 (July 2012–November 2012), the higher in-strength (with gray line) of the UK stock market confirms that other 45 stock markets exert persist greater adjustment coefficients, indicating that they respond to their short-run deviations from long-run equilibrium path with the UK stock market profoundly. In other words, the short-run error correction effect of the UK stock market is weak during the three rounds of BoE's QE. However, the out-strength (with red line) of the UK market appears to rise sharply during the August 2011. This confirms the short-run error adjustments for restoring the long-run equilibrium fall again on the stock market of UK, since stock markets around the world crashed due to fears over the European sovereign debt crisis in August 2011. Moreover, the relative higher out-strength (with red line) of the UK stock market in Fig. 4.10(a) further illustrates that the British stock market respond to correct its deviation and converge towards the long-run equilibrium with other 45 stock markets significantly during the year of 2013, October 2014 and January 2016, respectively. Particularly, the 45 stock markets adjusted more quickly to return to their long-run equilibrium with the UK market than the opposite direction during the August 2015 and from February till June 2016. The later is contribute to the British government announced that the UK leaving the European Union would be held on 23 June 2016.

In summary, in Fig. 4.10(a)), the UK stock market exhibits stronger error self-correction mechanism during the recent financial crises, more specifically, the dramatical rises were found after October 2007 and September 2008 along with the Northern Rock crisis in the UK and 2007–09 Global Financial Crisis. Furthermore, differ from the short-run error adjustment effects of the US stock market, in August 2011, during the most serious phase of European sovereign debt crisis, the UK stock market has a more significant error correction of its deviation to restore the long-run equilibrium with other 45 national stock markets. While the reverse direction of self-stabilization adjustment fell on the other 45 national stock markets as the result of the corresponding announcements and implementations of BoE's QE1, QE2, and QE3. Accordingly, the findings further confirm the presence of a weaker self-adjustment mechanism of the UK stock market during its own QE activities. A further observation is, that the statistically significant results in Fig. 4.10(a)) support the existence of steady long-run cointegrating relationships between the UK and other 45 national stock markets, and quantitatively measured through the out- and in-degree of the UK stock market in Fig. 4.10(b). Consisting with the findings in Fig. 4.10(a), the number of the long-run cointegrations between the UK and other 45 national stock markets experience persistent rise before the financial crises and start to decline after the financial turbulence. In particular, the UK stock market has higher out-degree (with red line) than in-degree (with gray line) through phases of financial turmoil over 2007-17, especially, during the Northern Rock crisis, 2007–09 Global Financial Crisis, as well as the European debt crisis in August 2011. The interesting finding is that, the in-degree of the UK stock market is greater than that of the out-degree during the 2010 Greek debt crisis, and when the UK referendum date was announced and implemented in February and June 2016 respectively. Moreover, comparatively, there exist more long-run equilibrium relationships amongst the UK and other 45 national stock markets when the outbreak of the debt crisis in the Eurozone (i.e., the 2010 Greek and 2011 European debt crisis) than that of the US stock market.

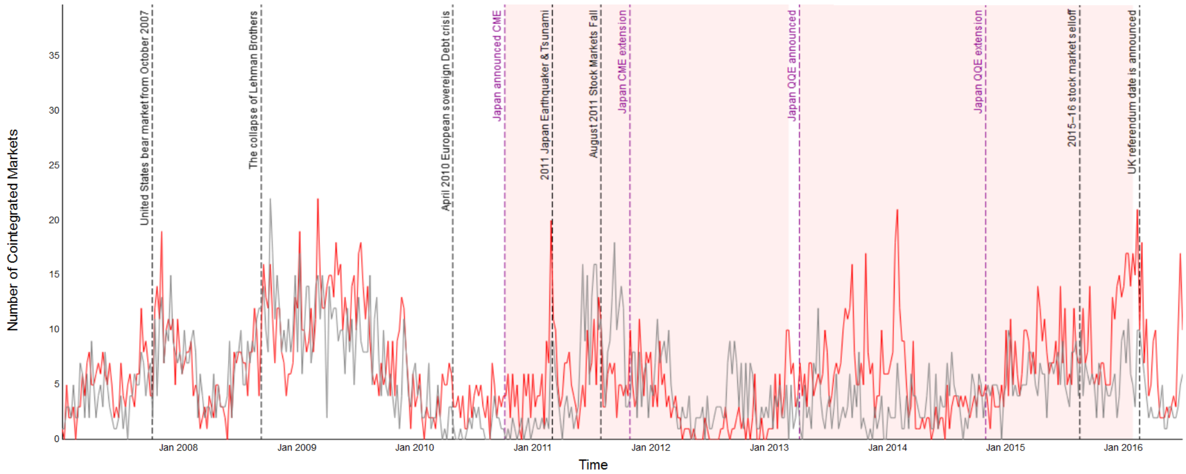
It is likely to state that due to the geographical proximate, the UK stock market tends to react to the debt crisis more serious than the US stock market.

Case Study of the Japanese Stock Market

Further, facing 2007–09 Global Financial Crisis, the persistent deflation and a policy rate at the lower bound, the BoJ announced a new Comprehensive Monetary Easing (CME) policy on 5 October 2010 and extended on October 2011 (the first red region in the Fig. 4.11) to stimulate the domestic economy. In the following year of April 2013, the BoJ's quantitative and qualitative easing (i.e., QQE) policies conducted (the second red region in the Fig. 4.11) aim to overcome the prolonged deflation that has gripped Japan. The BoJ expanded its bond purchase programme of QQE in October 2014 (the second red region in the Fig. 4.11) due to tax increases in April 2014 and lower crude oil prices [20, 107]. In order to assess the evolutionary short-run error adjustment effects between Japanese stock market and the other 45 national stock markets, both total out- and in-strength, total out- and in-degree of the NIKKEI 225 index are displayed in Fig. 4.11(a) and Fig. 4.11(b) respectively.



(a) Total out-strength (red line) and in-strength (gray line) of the Japanese stock market



(b) Total out-degree (red line) and in-degree (gray line) of the Japanese stock market

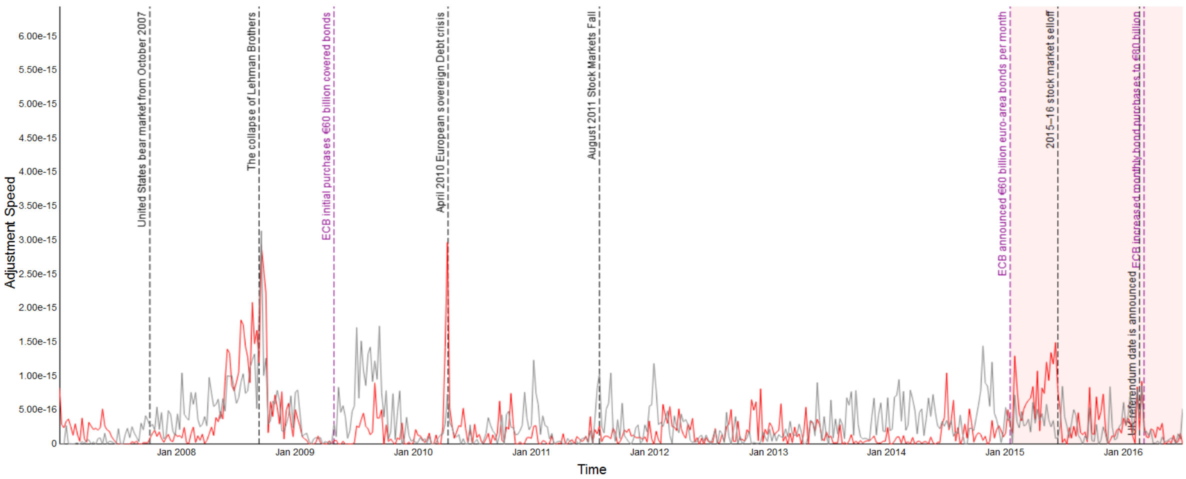
Fig. 4.11. Dynamic short-run error adjustment effects and long-run equilibrium relationships between the Japanese and other 45 national stock markets. The red regions depict corresponding duration of QEs in the Japan. The purple vertical dashed lines represent the announcement, extension and end dates of corresponding BOJ QEs. The black vertical dashed lines show the dates of the financial turmoils.

In Fig. 4.11(a), we can observe that the out-strength (with red line) of the Japanese stock market increased slightly during October 2007 since the start of the financial turmoil caused by the US sub-prime crisis. An interesting finding is that its in-strength (with gray line) was higher than the out-strength (with gray line) for Japanese stock market during the bankrupt of Lehman brother in September 2008. However, a dramatically rose of its out-strength (with red line) from March 2009 till November 2009, which means there were a strong disequilibrium self-correction effects for the stock market of Japan to maintain the long-run cointegration with other 45 stock markets. The reason seems to be apparent, the failure of Lehman Brothers in September 2008 triggered the worst economic turmoil worldwide, the smaller out-strength of the Japanese stock market indicates its weaker error self-adjustment effects during this period. Conversely, the persistent higher out-strength of the Japanese market from January 2009 to January 2010, which means that the Japanese stock market is expected to be more liquid and efficient, and it quickly responds to its deviations and to maintain long-run equilibrium relations with other 45 national stock markets. Notably, the Great East Japan Earthquake that occurred in March 2011 caused the Japanese stock market changed significantly to react its disequilibrium and pull the long-run equilibrium exist with other 45 national stock market quickly. Likewise, the strong self-correction effects of the Japanese stock market happened during the BoJ's QQE announcement and extension periods. The similar situation happened over 2015–16 global financial turbulence, as well as the UK government, announced the European Union membership referendum in February 2016, we find that the short-run deviations fell on the stock market of Japan to react for maintaining the long-run equilibrium relations with other 45 national stock market.

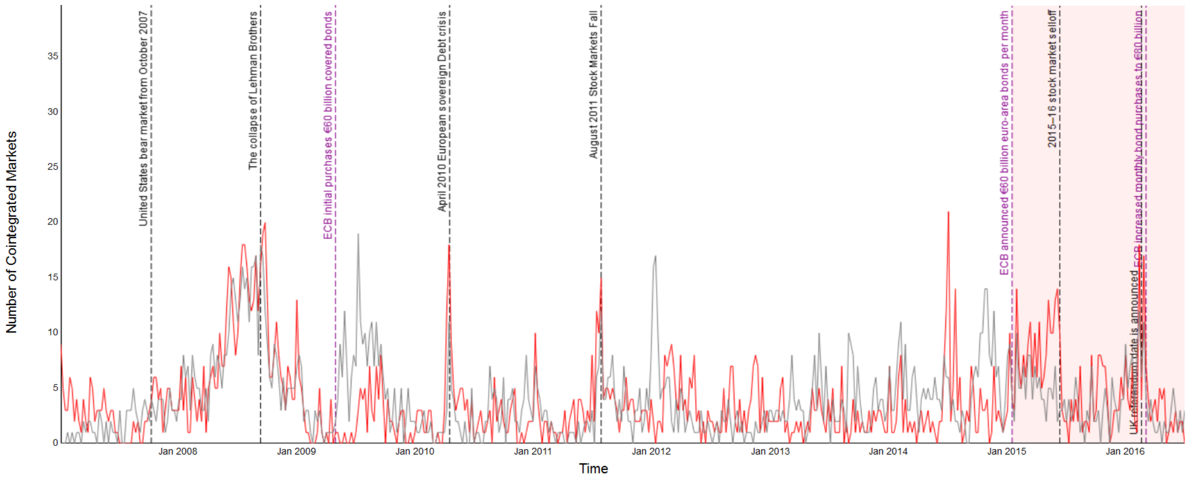
A further observation is, that the statistically significant results in Fig. 4.11(a)) support the existence of steady long-run cointegrating relationships between Japan and other 45 national stock markets. Specifically, in Fig. 4.11(b), the number of cointegration relations are quantitatively measured through the out- and in-degree of the Japanese stock market. There is a clear picture of an increase in the number of cointegration relationships during various phases of financial turmoil throughout the periods 2007–17. In particular, more long-run equilibrium relations exist since the US bear market from October 2007, after the collapse of Lehman Brother until the end of the year 2009, the Great East Japan Earthquake that occurred in March 2011, the 2015-16 global financial turbulence, as well as the EU Referendum announced by British government in February 2016. With respect to the BoJ's QE activities, that the number of cointegration rose notably during the implementation and extension phases of QQE.

Case Study of the "PIIGS" Stock Markets

With respect to the stock markets of the "PIIGS" countries in the Eurozone, the Fig. 4.12–Fig. 4.16 illustrate the time-varying out- and in-strength, out- and in-degree regarding the stock markets of Portugal, Italy, Ireland, Greece, and Spain, respectively. This could lead us to investigate how dynamic short-run error adjustment effects differ from the "PIIGS" stock markets from the evolutionary perspective. Since 2007–09 Global Financial Crisis and sovereign debt crisis that happened in the Euro-Area, the European Central Bank (ECB) has been very active to avoid the complete meltdown of their financial sectors and limit the adverse consequences for the real economy. Specifically, the ECB signaled that its initial purchases of covered bonds would be worth about €60 billion in May 2009. Following the lead of the US Fed, BoE and BoJ, the ECB announced the QE in January 2015, with a scale of about €1.1 trillion, and bought €60 billion treasury bonds and other bonds every month starting from March 2015 (as presented by the red regions in the Fig. 4.12–Fig. 4.16) [20, 107].



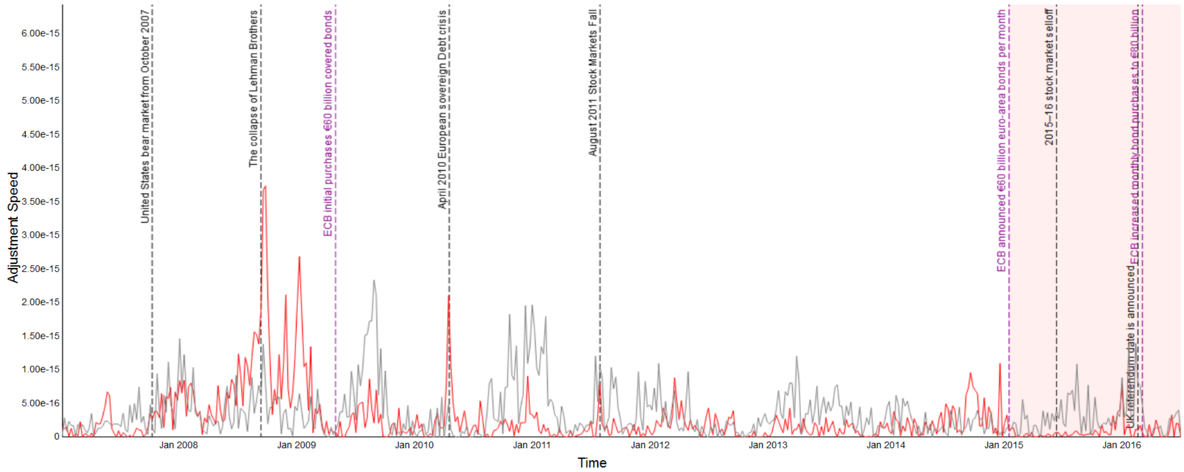
(a) Total out-strength (red line) and in-strength (gray line) of the Portugal stock market



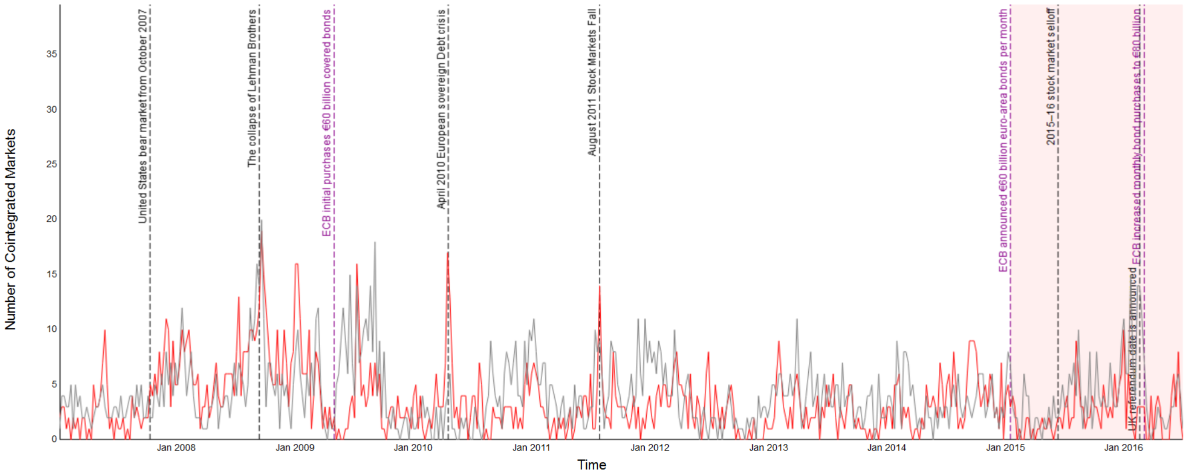
(b) Total out-degree (red line) and in-degree (gray line) of the Portugal stock market

Fig. 4.12. Dynamic short-run error adjustment effects and long-run equilibrium relationships between Portugal and other 45 national stock markets. The red regions depict corresponding duration of QEs in the Europe. The purple vertical dashed lines represent the announcement, extension and end dates of corresponding ECB QEs. The black vertical dashed lines show the dates of the financial turmoils.

From Fig. 4.12(a)–Fig. 4.16(a), the varied significant short-run self-adjustment effects show higher heterogeneity of the five "PIIGS" stock markets, by observing the corresponding out- and in-strength of the respective countries' stock market, respectively. Specifically, comparing the out-strength (with red line) of the "PIIGS" stock markets from Fig. 4.12(a)–Fig. 4.16(a), we find that when facing the Great Recession of 2007–09, particularly, after the collapse of Lehman Brothers in September 2008, the stock markets of Italy and Ireland had more evident self-regulating correction effects than the Portuguese, Greek, and Spanish stock markets to force the long-run equilibrium back. We also note that there was a slight rise of the out-strength (with red line) happened during the April 2010, namely, during the Greek sovereign debt crisis, which indicate that both "PIIGS" stock markets exert notably short-run deviation adjustment effects, whilst stock markets of Portugal, Ireland, and especially, Greece have stronger short-run error self-adjustment effects than that of the Italian and Spanish stock markets.



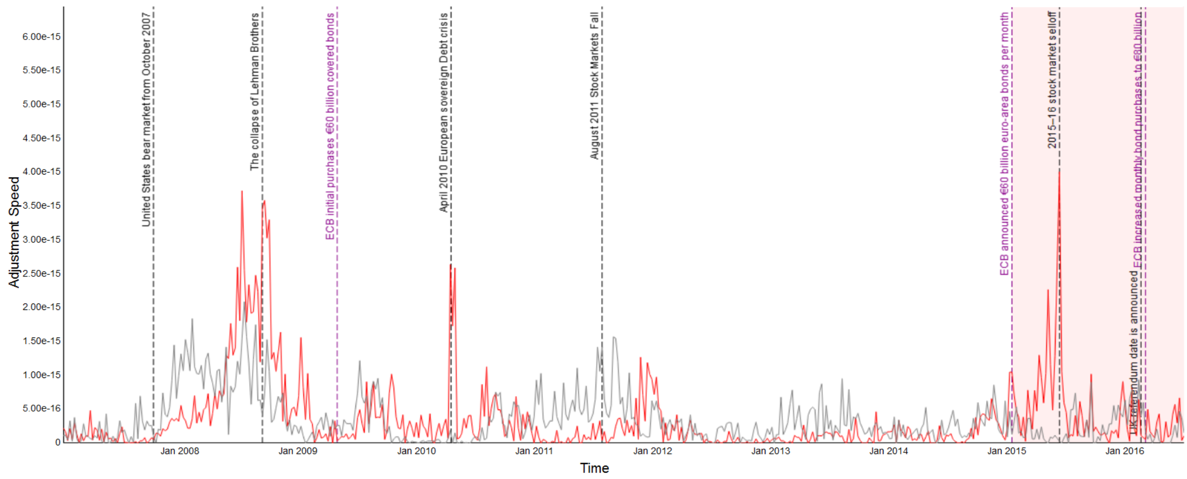
(a) Total out-strength (red line) and in-strength (gray line) of the Italy stock market



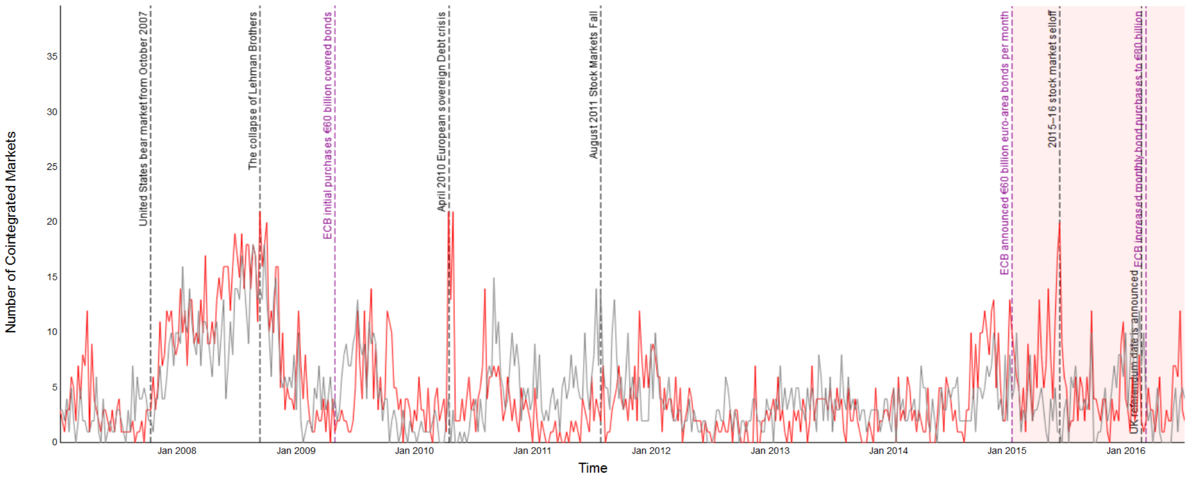
(b) Total out-degree (red line) and in-degree (gray line) of the Italy stock market

Fig. 4.13. Dynamic short-run error adjustment effects and long-run equilibrium relationships between Italy and other 45 national stock markets. The red regions depict corresponding duration of QEs in the Europe. The purple vertical dashed lines represent the announcement, extension and end dates of corresponding ECB QEs. The black vertical dashed lines show the dates of the financial turmoils.

Conversely, both of the "PIIGS" stock markets have the larger in-strength (with gray line) than the out-strength (with red line) from May 2009 until October 2009, which might be explained by the ECB launched its intent to purchase €60 billion in covered bonds in May 2009 as well as caused by the announcement of the Great Recession officially ending in June 2009. Similar significant results are associated with the sharp drop in stock prices in stock exchanges across the US, Middle East, Europe and Asia during August 2011, both of these five "PIIGS" stock markets have weaker self-correction effects to maintain the long-run equilibrium relations with other national stock markets. These findings further confirm that during the mentioned periods, the self-correction of short-run departures fall on other national stock markets, and they react to maintain the long-run equilibrium with stock markets of Portugal, Ireland, Italy, Greece, and Spain, respectively. In other words, they respond to their disequilibrium and share common stochastic trend with the stock markets of "PIIGS" countries. With regarding the ECB's introduction of QE from January 2015, the stock markets of Portugal, Ireland, Greece have persisted higher out-strength (with red line) throughout that period, which highlights that they respond swiftly to their deviations to pull the long-run equilibrium come back after the short-run deviations. The opposite findings happened for the Spanish and Italian stock market, other 45 stock markets respond to their short-run departures and maintain the equilibrium relations with them respectively. Finally, it can be seen that during the February 2016, namely, the announcement of "UK Referendum of Leaving EU", except the Italian stock market, other four "PIIGS" stock markets react to their short-run deviations quickly to restore the long-run equilibrium in the system.



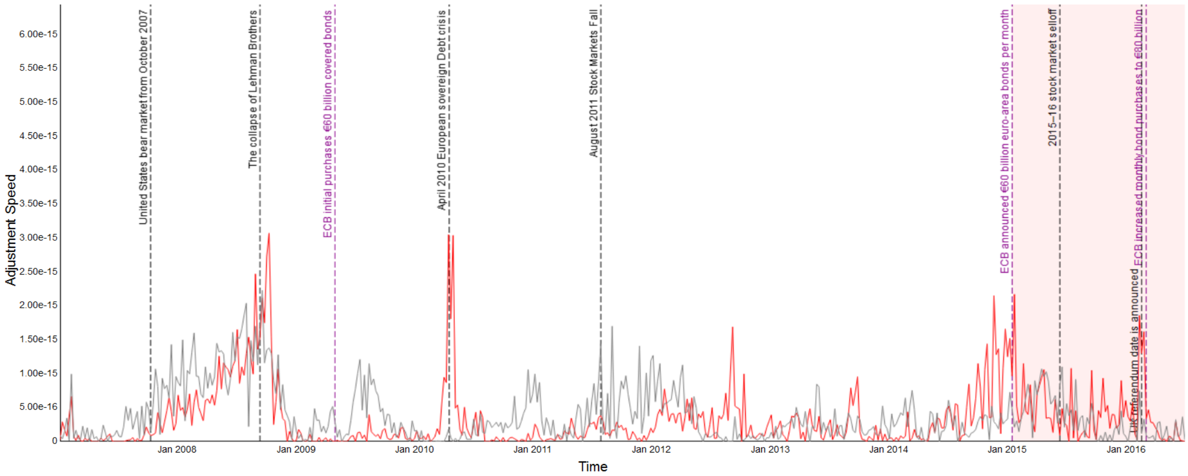
(a) Total out-strength (red line) and in-strength (gray line) of the Ireland stock market



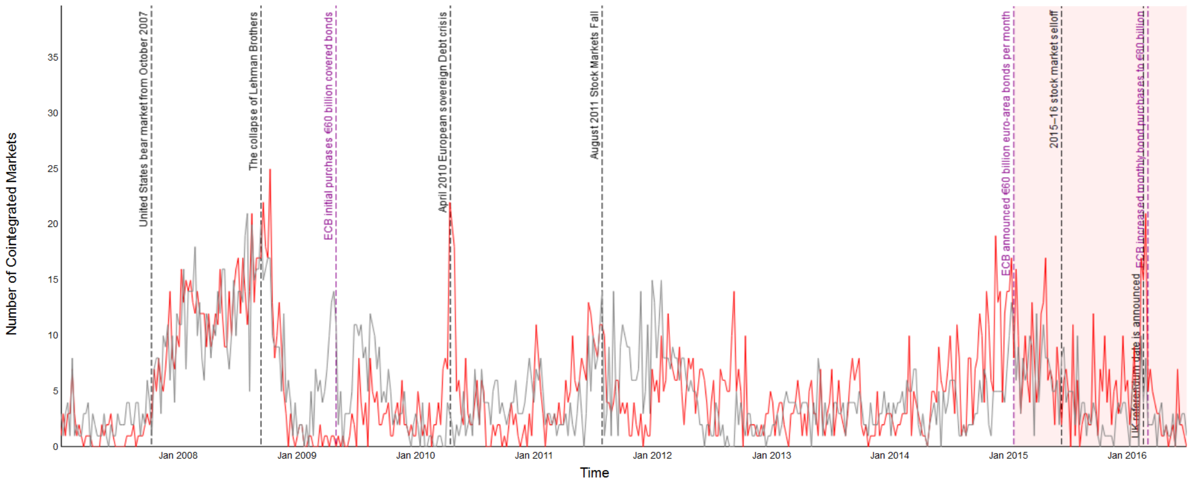
(b) Total out-degree (red line) and in-degree (gray line) of the Ireland stock market

Fig. 4.14. Dynamic short-run error adjustment effects and long-run equilibrium relationships between Ireland and other 45 national stock markets. The red regions depict corresponding duration of QEs in the Europe. The purple vertical dashed lines represent the announcement, extension and end dates of corresponding ECB QEs. The black vertical dashed lines show the dates of the financial turmoils.

Afterward, since the significant error correction effects (the out- and in-strength of each stock market in Fig. 4.12(a)–Fig. 4.16(a)) of the five "PIIGS" stock markets further confirm the presence of the steady long-run equilibrium relationships. As depicted from Fig. 4.12(b)–Fig. 4.16(b), the varied number of cointegral relations is quantitatively measured through the out- and in-degree of the stock markets in "PIIGS" countries,, respectively. By comparing the Fig. 4.12(b)–Fig. 4.16(b), we can observe that the number of the significant cointegration relations increased notably during the periods of financial turmoil, especially during the phases of post-Lehman Brothers failure as well as the following sovereign debt crisis happened in Europe. Besides, there existed more long-run cointegration relations amongst "PIIGS" stock markets (except the stock markets of Italy and Spain) after the ECB announced the QE in January 2015. Further, more significant cointegration is found for both five “PIIGS” stock markets with other national stock markets during the February 2016 owing to the fear over the uncertainty of the British government announced the date of the referendum.

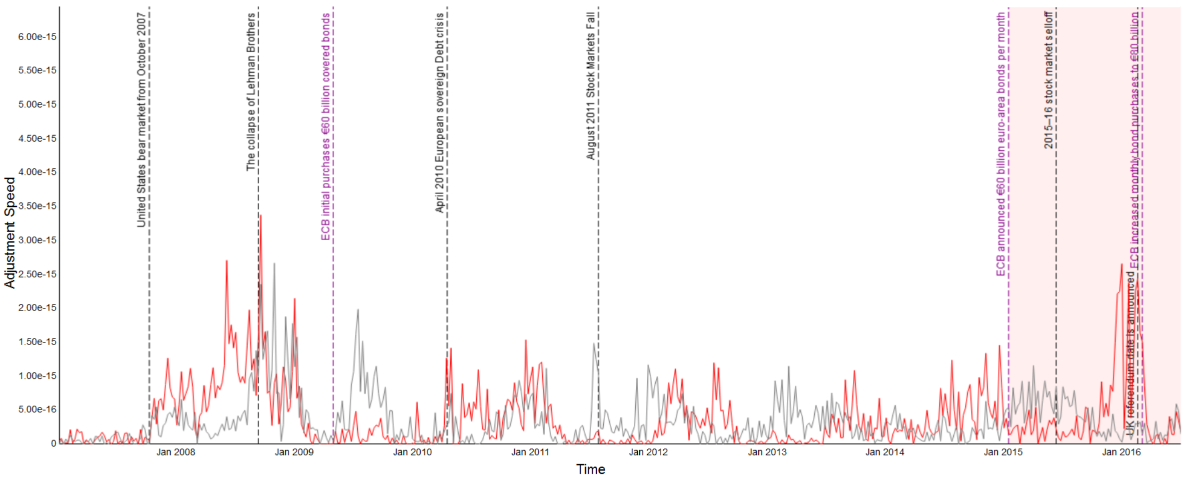


(a) Total out-strength (red line) and in-strength (gray line) of the Greece stock market

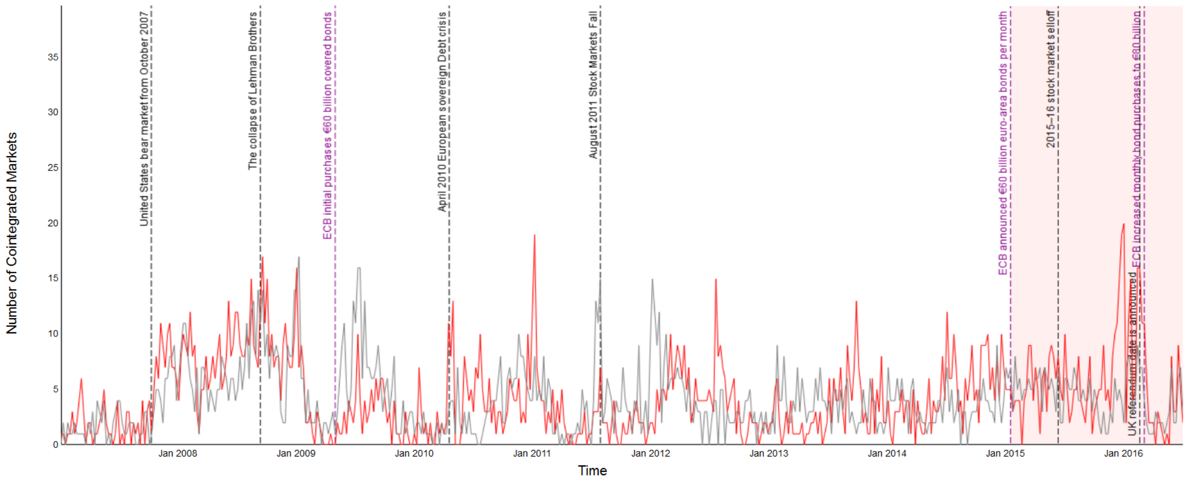


(b) Total out-degree (red line) and in-degree (gray line) of the Greece stock market

Fig. 4.15. Dynamic short-run error adjustment effects and long-run equilibrium relationships between Greece and other 45 national stock markets. The red regions depict corresponding duration of QEs in the Europe. The purple vertical dashed lines represent the announcement, extension and end dates of corresponding ECB QEs. The black vertical dashed lines show the dates of the financial turmoils.



(a) Total out-strength (red line) and in-strength (gray line) of the Spain stock market



(b) Total out-degree (red line) and in-degree (gray line) of the Spain stock market

Fig. 4.16. Dynamic short-run error adjustment effects and long-run equilibrium relationships between Spain and other 45 national stock markets. The red regions depict corresponding duration of QEs in the Europe. The purple vertical dashed lines represent the announcement, extension and end dates of corresponding ECB QEs. The black vertical dashed lines show the dates of the financial turmoils.

In sum, our case studies of the US, UK, Japanese, and "PIIGS" countries' stock markets revel highly heterogeneity related to the short-run error self-adjustment effects, as well as long-run equilibrium relationships under the impact of the financial turmoil and QE activities over the period 2017–17. Our observations from Fig. 4.9 to Fig. 4.16 suggest that both of the US and UK stock markets exert the quickest short-run error self-adjustment speed during the Lehman Brother collapse in September 2008 than that of the stock markets of Japan and "PIIGS" countries. However, during the period of Northern Rock crisis in October 2007 and European sovereign debt crisis in August 2011, the UK stock market reacts swiftly to its short-run deviations for maintaining the long-run equilibrium than that stock markets of US, Japan and "PIIGS" countries. For the stock market of Japan, the findings of the persistent and faster self-adjustment effects observed from January 2009 to January 2010, as well as associated with Great East Japan Earthquake in 2011. Comparatively, the five "PIIGS" stock markets show more significant short-run error correction effects than the US, UK, and Japanese stock markets during the Greek sovereign debt crisis in 2010. In particular, the stock markets of Greece and Spain response evidently since the EU referendum accounted by the UK in February 2016. It should be noted that, by comparing the QE activities announced and implemented by the Fed, BoE, BoJ, and the ECB, different error correction effects and long-run cointegration amongst the global stock markets could be found significantly under study. The US stock market bears the brunt of short-run error adjustment to bring about the long-run equilibrium with other stock markets during the announcement and implementation of the US QE1 (from December 2008 until March 2009), the OT (from December 2011 until mid-2012), as well as the announcement of QE3 tapering. Similar results can be found in Japanese stock market, which shows that during the implementation and extension phases of the BoJ's QQE, the short-run error adjustments for restoring the long-run equilibrium fall on the stock market of Japan. By contrast, the UK stock market only has slightly response related to its corresponding QE activities. As for the "PIIGS" countries, except the stock markets of Spain and Italy, both of the stock markets in the Greece, Portugal, and Ireland have a quick reaction of their short-run departures to maintain the long-run equilibrium with other national stock markets during the implementation of QE by the ECB since 2015.

4.7 Conclusions

In this chapter, we investigate the short-run disequilibrium adjustment effects and long-run equilibrium amongst international stock markets based on the complex network theory and econometric measures (i.e., cointegration and error correction models) between 2007 and 2017. Specifically, weekly data for the period of January 2007–June 2017 are utilized across as many as the 46 stock market indices within the MSCI ACWI index to cover the recent economic and financial crises, as well as QE activities. To consider the topological changes of the international stock markets, we build up the static and dynamic networks of the international stock markets and utilize the average strength and degree, network density, clustering coefficient, reciprocity and average path length to detect the variation of the network topological structure as a function of time. Finally, this chapter aims to examine whether the effects of the recent financial crises, as well as the occurrence and intensive of the QE activities, were more operative on potential linkages among international stock markets.

The empirical findings can be summarized as follows: First, through the static analysis of the international stock markets network over the period 2007–17, allowing us to ensure that the short-run deviation adjustment effect, and the long-run equilibrium relationships between the emerging stock markets from the areas of Asia-Pacific, Middle East, Africa and Latin America, have become deepened since the recent global financial crises started from 2007. Particularly, most of the stock markets from Europe formed a community, while connections between them become more heterogeneous. While the "PIIGS" countries which include the stock markets of Portugal, Italy, Ireland, Greece and Spain clustered significantly. Furthermore, the evolutionary results of the dynamic networks demonstrate that short-run error adjustment effects and long-run equilibrium amongst the 46 stock markets have changed considerably over time. Our investigated time-varying network metrics combined could serve as a useful risk indicator to reflect both financial tranquil and turmoil phases from 2007 to 2017. Finally, we note that the case studies of the US, UK, Japanese, and "PIIGS" countries' stock markets distinguish that, the extent of short-run error self-adjustment effects, as well as the long-run equilibrium significantly, varies across different markets under the influence of financial turbulence and QE activities retrospectively.

Chapter 5

Sector Analysis of British Stock Market based on Minimum Spanning Tree and Hierarchical Clustering

Abstract: In this chapter, we analyze the financial effects of Brexit-vote shock on the stocks listed on the London Stock Exchange (FTSE 100 and FTSE Mid250 Index). Specifically, we construct corresponding British stock networks using the cointegration-based error correction models to investigate the short-run self-correction mechanism as well as long-run equilibrium amongst stocks in sector-level before and after one-year of the Brexit-vote. Subsequently, to extract as much information as possible from the stock networks, the minimal spanning tree (MST) and hierarchical clustering analysis are employed for filtering networks and to detect the taxonomy and hierarchical topological structure based our proposed Jaccard distance metric. The empirical evidence indicates that the Financials, Consumer Goods, Consumer Services have more significant short-run error self-adjustment effects to maintain the steady equilibrium state compared to the sectors from Industrials, Basic Materials, Utilities, and Telecommunications over the entire period from 2007 to 2017. The obtained results of the MSTs reveal that stocks from the Financials, Consumer Services, Consumer Goods, Industrials, Health Care located in the center of the MSTs, while most of the stocks from Utilities, Technology, and Telecommunications are located in the periphery of the MSTs. Ultimately, the largest community detected from the hierarchical clustering analysis highlights the significant response of Banks, Real Estate Investment & Services, Real Estate Investment Trusts caused by the financial uncertainty of after the Brexit-vote.

5.1 Introduction

On June 23, 2016, the British government officially announced that the United Kingdom voted to leave the European Union, what is commonly known as “Brexit”. One significant impact of this political and financial uncertainty is that the UK Sterling weakened sharply and remained substantially below its pre-Brexit level [24]. However, in the UK stock market, the FTSE 100 index did not fall as much as the mid-cap FTSE 250 index after the Brexit vote, since roughly 70% of revenue made by the companies from FTSE 100 index is generated abroad and benefiting from the weaker pound. In particular, the shares of companies with more foreign sales suffered less from the announcement of the Brexit referendum [25]. Generally, individual stock price movement is dependent upon economic fundamentals of the companies as well as investors’ preferences, and several other factors such as important news and extreme financial or political events. What’s more, a large number of heterogeneous interaction elements in the stock market, leading to complex mutual interdependencies that further influences the behavior of stock prices. Thus, to characterize and interpret the complex behavior in the stock market, the financial and economic networks have gained attention to facilitate insights into the complexities and the internal structure of connectedness in the stock market [3].

On the other hand, economic conditions vary across sectors, especially during the phases of the financial and political disturbance. Several studies assessed the financial effects of Brexit-vote on the UK stock market and indicated that the economic sectors such as Banks, Financial Services, Defense &Airlines, Travel & Leisure, Real Estate and Technology, ect., were affected the most than other industrial sectors after the Brexit [110, 111]. Since sector considerations give critical insights into how to design and deliver policy in the economic development, therefore, it has been became essential to understand the internal dependencies among stock prices at sectoral level in a network form. In this chapter, the stock networks are built up using the error correction models (ECM) [14–16], which allow us to capture not only the short-run error self-adjustment effects of the British stocks, but also reveal the long-run equilibrium interdependence among stocks from a complex system perspective. Particularly, one should be aware that, in general, the resulting networks constructed based on ECM models are usually relatively complex even after the BH statistical validation tests with the FDR $\alpha = 0.01$. In order to reduce the complexity of the ECM-based stock networks, we apply the minimal spanning tree (MST) technique, which is methodologically straightforward approach to filter important information and to analyze the strongly related topological structure of the British stock networks [6].

It is well known that analyzing the topological MSTs structure of the stock market, a distance metric is need to define. Since [4] proposed a distance function based on Pearson correlation coefficients between pairwise financial asset returns, it has been used in a considerable number of works for constructing MSTs to investigate the complex structure of financial market [5, 7, 26–28]. Here, another distance metric, the Jaccard distance that evaluated from our constructed directed and weighted ECM-based stock network is proposed in this chapter.

Finally, another contribution in this chapter emphases on detecting the community structure from the UK stock networks through hierarchical clustering algorithm to mine the sets of stocks which having common properties. According to [112, 113], complex networks have community structure if the nodes of the networks can be grouped into sets of closely related nodes where each set of nodes is densely connected among each other and loose connections to others. Here, we are interested in discovering if the constituents of the FTSE 100 and FTSE Mid250 that traded on London Stock Exchange (LSE) do share common stochastic trends to move together, and whether groups of stocks that co-movement are identifiable in terms of industrial activity owing to the effects of the Brexit-vote. To sum up, based on our proposed Jaccard distance metric, the hierarchical clustering methods have been performed on recognition of the topological structure of the UK stock market pre- and post-the Brexit vote, respectively.

The remainder of this chapter is structured as follows. In Subsection 5.2, the methodologies to be adopted are presented in greater detail. In Subsection 5.3 the data are discussed. Subsection 5.4–5.6 holds the empirical analysis and provides the results. In Subsection 5.7, a conclusion based on the empirical results is presented, along with suggestions of future research.

5.2 Network Representation of the UK Stock Market

In ECM models, what we are most interested in is the respective error correction coefficients. If the estimated error correction parameters between pairwise stocks are significant as expected after the Statistically Validation Test described in Chapter 2, we then build up the corresponding ECM-based British stock market networks.

Let a graph $G(V, E, W)$ represents the directed and weighted ECM-based stock network, where V is sets of vertices which denotes the various stocks, E is sets of edges that represents the short-run error correction effects and long-run cointegration between each pair of stocks. Each network edge is assigned weight W, is the error adjustment coefficients between each pair of stocks. Specifically, if a stock i reacts to restore disequilibrium to maintain the long-run equilibrium towards j, then a directed link is drawn from i to j. The adjacent matrix W of the British stock network can be represented as follows

$$W_{i\to j} = \begin{cases} w_{ij}, & i \text{ responses to its short run deviations to restore cointegration with } j \\ 0, & \text{otherwise} \end{cases} \tag{5.1}$$

The magnitude of w_{ij}, namely, the error correction coefficients indicate the speed of deviations of stock i from long-run equilibrium will feed-back on the change in the i in order to force the movement towards the long-run equilibrium with j. It should be noted that the significant short-run error adjustment effects between stocks further confirm the existence of a cointegration relationship between pairwise stocks in the UK market.

5.2.1 Jaccard Distance Metric

Since nodes in the complex network might receive common news and tend to connect together, the Common Neighbor (CN) (Lorrain1977) index is the simplest method to measure node similarity by directly counting the overlap of news received. Based on the concept of the CN index, the Jaccard similarity coefficient, i.e., Jaccard index [114], measuring the proportion of shared nodes between i and j relative to the total number of nodes connected to i or j. More specifically, the Jaccard similarity coefficient J_{ij} is defined as the size of the intersection divided by the size of the union of the sample set:

$$J_{ij} = \frac{\Gamma(i) \cap \Gamma(j)}{\Gamma(i) \cup \Gamma(j)}, (0 \leq J_{ij} \leq 1), \tag{5.2}$$

where $\Gamma(i)$ and $\Gamma(j)$ are the sets of nodes that are neighbors of i and j respectively. The term $\Gamma(i) \cap \Gamma(j)$ is the number of neighbors that i and j have in common, and the $\Gamma(i) \cup \Gamma(j)$ represents the total number of neighbors that i and j have. In general, the greater the Jaccard similarity coefficient, the more common properties between i and j. Then the Jaccard dissimilarity coefficient, namely, the Jaccard distance d_{ij} could be expressed as

$$d_{ij} = 1 - J_{ij}, (0 \leq d_{ij} \leq 1). \tag{5.3}$$

With respect to our constructed ECM-based stock network is directed and weighted, here, we propose a modified Jaccard distance. The method we present consists of two steps. Firstly, assigning for each node a weighted degree, $k_i^{'}$:

$$k_i^{'} = [k_i^{\alpha}(\sum_j^{k_i} w_{ij})^{\beta}]^{\frac{1}{\alpha+\beta}}, \tag{5.4}$$

where k_i is the degree of node i, and $\sum_j^{k_i} w_{ij}$ is the sum over all its link weights. In the present study we discuss only the case where $\alpha = \beta = 1$, which treats the weight and the degree equally in the network. Then the new weighted degree $k_i^{'}$ is presented as follows [115]

$$k_i^{'} = \sqrt{k_i \sum_j^{k_i} w_{ij}}. \tag{5.5}$$

Secondly, in the directed network, if there is a link from node i to node j, i is the in-neighbor of j, and correspondingly, j is out-neighbor of i. Therefore, the Jaccard similarity coefficient based on in-neighbors is descried as

$$J_{ij}^{in} = \frac{\Gamma^{in}(i) \cap \Gamma^{in}(j)}{\Gamma^{in}(i) \cup \Gamma^{in}(j)}, (0 \leq J_{ij}^{in} \leq 1), \tag{5.6}$$

where the $\Gamma^{in}(i) = \Big\{w|(w,i) \in E\Big\}$ and $\Gamma^{in}(j) = \Big\{w|(w,j) \in E\Big\}$ are the sets of in-neighbors of nodes i and j, respectively. The term $\Gamma^{in}(i) \cap \Gamma^{in}(j)$ counts the number of in-neighbors that i and j have in common. The $\Gamma^{in}(i) \cup \Gamma^{in}(j)$ calculates the total number of corresponding in-neighbors of i and j. Then, the corresponding Jaccard distance based on in-neighbors can be represented as

$$d_{ij}^{in} = 1 - J_{ij}^{in}, (0 \leq d_{ij}^{in} \leq 1). \tag{5.7}$$

In contrast to that, the Jaccard similarity coefficient based on the out-neighbors is descried as

$$J_{ij}^{out} = \frac{\Gamma^{out}(i) \cap \Gamma^{out}(j)}{\Gamma^{out}(i) \cup \Gamma^{out}(j)}, (0 \leq J_{ij}^{out} \leq 1), \tag{5.8}$$

where the $\Gamma^{out}(i) = \Big\{w|(i,w) \in E\Big\}$ and $\Gamma^{out}(j) = \Big\{w|(j,w) \in E\Big\}$ receptively represent the sets of out-neighbors of nodes i and j. The $\Gamma^{in}(i) \cup \Gamma^{in}(j)$ calculates the total number of out-neighbors of i and j. The Jaccard distance based on out-neighbors can be presented as

$$d_{ij}^{out} = 1 - J_{ij}^{out}, (0 \leq d_{ij}^{out} \leq 1). \tag{5.9}$$

Overall, the Jaccard distance varies from 0 to 1 with small distances correspond to high Jaccard similarity coefficients and vise versa. The smaller the distance (near zero) between any pair of stocks imply that information is similar across, while the greater the distance (near one) represents a situation in which two stocks are completely different. Furthermore, the Jaccard distance function of d_{ij}^{in} and d_{ij}^{out} both satisfy the axioms of a distance metric:

$$D1 : d(i,j) \geq 0, (\text{non-negative}) \tag{5.10}$$

$$D2 : d(i,j) = 0, \Leftrightarrow i = j, (\text{identity of indiscernibles}) \tag{5.11}$$

$$D3 : d(i,j) = d(j,i), (\text{symmetry}) \tag{5.12}$$

$$D4 : d(i,j) \leq d(i,k) + d(k,j), (\text{triangle inequality}) \tag{5.13}$$

The transformation of our proposed Jaccard distance approach creates an $N \times N$ distance matrix D from the $N \times N$ ECM-based stock network G. Based on our proposed Jaccard distance matrix D whose elements varies between 0 and 1, the MST, hierarchical clustering analysis could be conducted to better understand the topological structure of the British stock network, respectively.

5.2.2 Minimal Spanning Tree

For the reduction the complexity of the constructed ECM-based stock network, the maximal spanning tree (MST) has been used for filtering networks, resulting in simpler forms of graphs that can better facilitate analysis based on our proposed Jaccard distance matrix. Specifically, the MST constructs a topology network of connecting N stocks with

$N-1$ most important links which are of shortest distance. To construct the MST, each step for the widely used Kruskal's algorithm is presented as follows:

- Rank the $(N-1)N/2$ non-diagonal and upper/lower triangular elements of the Jaccard distance matrix in a non-decreasing order of their distance value.
- Pick the first element with the smallest Jaccard distance matrix in the ranked list and add it to the MST.
- Add the next element with a condition that no loops (cycles) are formed (i.e., the resulting network after adding the element is still a tree or forest). Else, discard it.
- Repeat the third step until all the elements in the spanning tree with $N-1$ links.

5.2.3 Community Detection with Agglomerative Hierarchical Clustering Algorithms

The cluster or community has been regarded as one of the most significant properties of complex networks. The hierarchical clustering method is widely applied network analysis tools and plays an important role in discovering the similar behaviors and features of stocks in the stock market [113, 116, 117]. Specifically, the hierarchical clustering is an iterative classification approach based on dissimilarities (distances) between the nodes to be grouped together. In this chapter, the hierarchical clustering analysis is performed by agglomerative algorithm [30], which is the "bottom-up" procedures:

- Start with each vertex in its own cluster.
- Iteratively merges the two closest clusters according to a given agglomeration criterion.
- Until all the vertices to into a single cluster.

As vertices merge into a small cluster in the procedures, three popular agglomeration criterion to evaluate the similarity of any pairs of clusters are called *single, average and complete cluster similarity linkage*, respectively [30]. Here, we define the Jaccard distance $d(M,N)$ between two clusters M and N, and then we merge in each step the two clusters M and N using the corresponding three linkage clustering methods.

Single Linkage Clustering

In single-link clustering, we consider the Jaccard distance between two clusters M and N to be equal to the shortest distance from any member of one cluster to any member of the other cluster, and can be presented as follow

$$d_{\text{single}}(M,N) = \min\left\{d(m,n) | m \in M, n \in N\right\}, \tag{5.14}$$

where $d(m, n)$ is the shortest Jaccard distance between members m and n in clusters M and N, respectively.

Average Linkage Clustering

As for the average linkage clustering, the Jaccard distance between two clusters M and N is equal to the average distance from any member of cluster M to any member of cluster N.

$$d_{\text{average}}(M, N) = \frac{1}{|M|\,|N|} \sum_{m \in M} \sum_{n \in N} d(m, n), \tag{5.15}$$

where $d(m, n)$ is the median distance between members m and n in clusters M and N, respectively.

Complete Linkage Clustering

Conversely with single linkage clustering, in complete linkage clustering, the Jaccard distance between one cluster and another cluster to be equal to the longest distance from any member of one cluster to any member of the other cluster, which can be presented as

$$d_{\text{complete}}(M, N) = \max\left\{d(m, n) | m \in M, n \in N\right\}, \tag{5.16}$$

where $d(m, n)$ is the maximal distance between members m and n in clusters M and N, respectively.

Since the pairwise mergers of clusters will eventually pull all vertices into a single cluster, then we can apply a dendrogram (i.e., tree diagram) to visually display the arrangement of the clusters produced by the hierarchical clustering algorithm [117].

5.3 Data Description

We choose the daily closing price for 350 stocks listed on the FTSE 100 and FTSE Mid250 Index, which represent the top and mid-cap stocks traded on the London Stock Exchange (LSE). The entire sample period used starts on 2 July 2007 and ends on 30 June 2017, and we select 279 stocks for which complete data are available during this period. In order to assess the financial impacts of the Brexit-vote on the UK stock market, the entire sample was divided into two 1-year sub-periods: (1) before Brexit-vote (1/6/2015–22/6/2016, with 338 stocks and 283 observations); (2) after Brexit-vote (23/6/2016–30/6/2017, with 348 stocks and 260 observations). All the data were collected from Datastream and transformed them into natural logarithms. Following the Industry Classification Benchmark (ICB) provided by FTSE International Ltd.,, all the stocks are classified into 12 industries and 37 sectors respectively. The list of industries, sectors and the corresponding number of stocks are summarized in Table. 5.1.

Table 5.1. List of 12 industries, 37 sectors and the corresponding number of stocks from FTSE 100 and FTSE Mid250.

Industry	**Sector**	**Number of Stocks**		
		Full sample	**Pre-Brexit**	**Post-Brexit**
Financials	Banks	5	9	11
	Equity Investment Instruments	32	43	43
	Financial Services (Sector)	18	21	21
	Life Insurance	6	8	8
	Nonlife Insurance	6	8	9
	Real Estate Investment & Services	8	9	9
	Real Estate Investment Trusts	15	18	18
Basic Materials	Chemicals	5	5	5
	Mining	11	15	15
	Industrial Metals & Mining	1	2	2
	Forestry & Paper	1	1	1
Consumer Goods	Automobiles & Parts	1	1	1
	Beverages	3	4	4
	Food Producers	5	5	5
	Household Goods & Home Construction	9	10	12
	Personal Goods	4	5	5
	Tobacco	2	2	2
Consumer Services	Food & Drug Retailers	5	6	6
	General Retailers	11	16	16
	Media	11	13	14
	Travel & Leisure	24	29	29
Health Care	Health Care Equipment & Services	2	5	5
	Pharmaceuticals & Biotechnology	8	9	9
Industrials	Aerospace & Defense	7	7	7
	Construction & Materials	4	6	7
	Electronic & Electrical Equipment	4	4	4
	General Industrials	6	6	6
	Industrial Engineering	6	6	6
	Industrial Transportation	4	5	5
	Support Services	30	32	33
Oil & Gas	Oil & Gas Producers	5	6	6
	Oil Equipment & Services	4	4	4
Technology	Software & Computer Services	5	6	8
Telecommunications	Fixed Line Telecommunications	2	3	3
	Mobile Telecommunications	2	2	2
Utilities	Electricity	2	2	2
	Gas, Water & Multiutilities	5	5	5
		279	338	348

5.4 Sector-level Analysis of the ECM-based Stock Networks

Before analyzing the effects of Brexit on the UK stock market, initially, we look at the topological structures of the stock networks based on the ECM models during the full sample from 2 July 2007 to 30 June 2017. From the respective of sector-level, the total-strength (in- and out-strength) and total-degree (in- and out-degree) of 37 economic sectors are depicted in Fig. 5.1 and 5.2 using spider plots respectively.

In Fig. 5.1, the results reveal that, over 2007–17, the companies from the sectors of Banks, Travel & Leisure, Support Services, Real Estate Investment Trust, Real Estate Investment & Services, Oil & Gas Producers, Life Insurance, Financial Services, Equity Investment Instruments have relative larger out-strength (with dashed blue lines in Fig. 5.1) than other sectors. The economic institution behind the findings is that the stocks belonging to these sectors response swiftly to their short-run deviations in the system and pull nonequilibrium back to the long-run equilibrium than other sectors in the UK stock market. In contrast to that, the economic sectors of Beverages, Automobiles & Parts, Oil Equipment & Services, Industrial Metals & Mining, Forestry & Paper, Fixed Line Telecommunications have a smallest out-strength (with dashed blue lines in Fig. 5.1), indicating that they response very slowly to their own short-run departures and take more time to restore the long-run equilibrium state.

With respect to the total in-strength (with solid yellow lines in Fig. 5.1) of each economic sector in the UK stock market, the sectors such as Travel & Leisure, Support Services, Media, Household Good & Home Construction, General Retailer, Financial Services, Equity Investment Instruments seem to exhibit the greater in-strength in the stock network of the British market. Differ from the greater out-strength of each economic sector, the greater in-strength of one sector highlights its previous period's change significantly caused other sectors quickly react their disequilibrium significantly to maintain the long-run equilibrium with it. Furthermore, the sectors of Banks, Oil Equipment & Services, Industrial Metals & Mining, Health Care Equipment & Services, Forestry & Paper, Fixed Line Telecommunication, Electricity have the smallest in-strength (with solid yellow lines in Fig. 5.1) in the UK stock market. The smaller in-strength of these sectors reveal that their change caused other sectors very slowly to react their disequilibrium to maintain the long-run equilibrium with them.

In particular, by comparing both in- and out-strength of each economic sector in Fig. 5.1, one can see that the industrial sectors of Banks, Real Estate Investment Trusts, Real Estate Investment & Services, Oil & Gas Producers, Life Insurance have higher out-strength while lower in-strength, respectively. As a result, the adjustment speeds of these economic sectors was confirmed by the larger out-strength and indicating they can adjust faster towards (disequilibrium) shocks to the system, while other sectors react their disequilibrium to maintain the long-run equilibrium with them very slowly. The economic logic behind these results suggests that these sectors are more liquid, efficient and integrated in the British stock markets than other sectors over the period from July 2007 to June 2017.

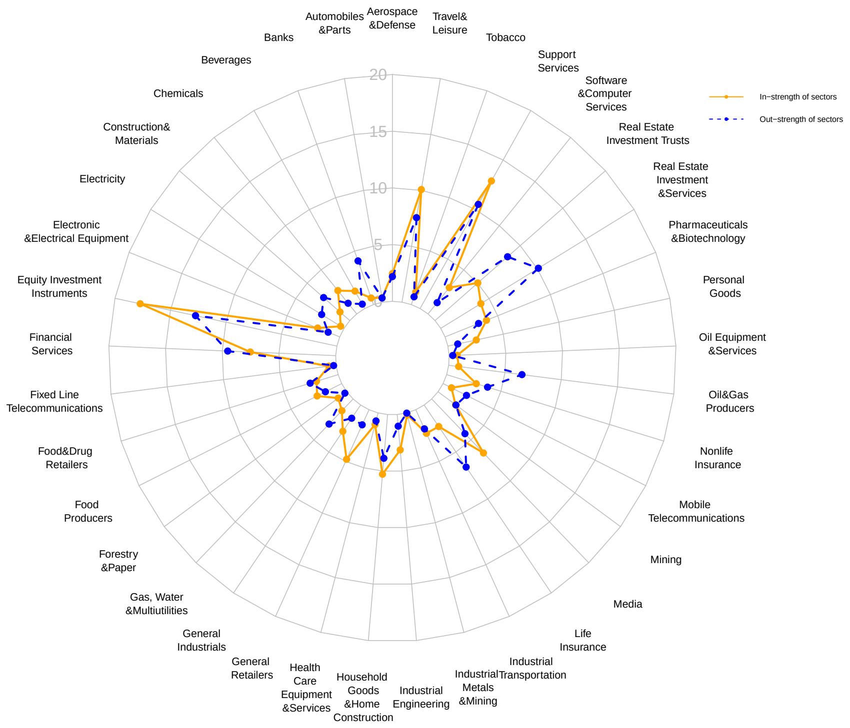


Fig. 5.1. In- and out-strength of each economic sector in the UK stock market from July 2007 to June 2017.

One the other hand, the significant in- and out-strength of each economic sector in Fig. 5.1 further support evidence of long-run equilibrium relations among the stocks from 2 July 2007 to 30 June 2017. The number of corresponding cointegral relations are depicted by the in- and out-degree of the network respectively in Fig. 5.2 using the radar plot. We can observe that the economic sectors of Travel & Leisure, Support Services, Real Estate Investment Trusts, Household Goods & Home Construction, General Retailers, Financial Services and Equity Investment Instruments both have higher out- and in-degree in the UK stock network. However, the sectors of Automobiles & Parts, Industrial Metals & Mining, Health Care Equipment & Services, Forestry & Paper, Fixed Line Telecommunications, Electricity, have the smallest in- and out- degree, respectively. Similarly to the obtained results from the Fig. 5.1, it is worth noticing that, over 2007–17, the economic sectors of Banks, Real Estate Investment Trusts, Mining have relatively higher out-degree while lower in-degree, respectively.

To sum up, the ECM-based stock networks based on sector-level analysis over the entire phase from July 2007–June 2017 imply that different industry sectors would behave differently in terms of the error correction mechanisms and long-run equilibrium relationships in the British stock market. From the results, we can find that the sectors belonging to Financials, Consumer Goods, Consumer Services have more significant adjustment effects to maintain the steady equilibrium state compared to the sectors from Industrials, Basic Materials, Utilities, and Telecommunications. This means that when the industries of Industrials, Basic Materials, Utilities, and Telecommunications have short-run deviates from equilibrium would last a longer time to return back to the equilibrium steady state, while the more efficient and integrated industries of Financials, Consumer Goods, Consumer Services response swiftly to correct their corresponding departures and maintain the long-run equilibrium with other industries in the British stock market.

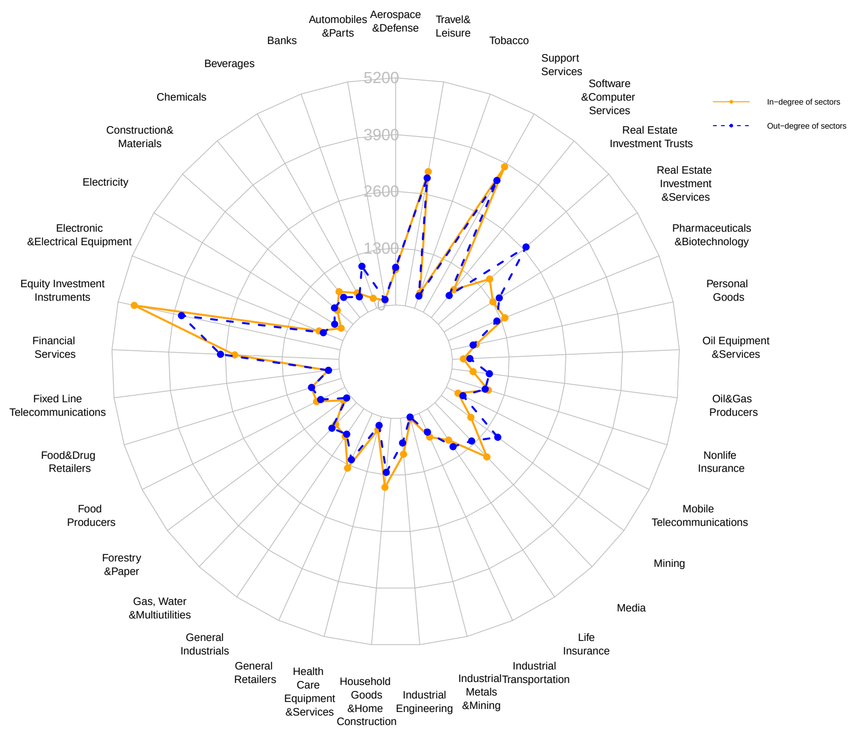


Fig. 5.2. In- and out-degree of each economic sector in the UK stock market from July 2007 to June 2017.

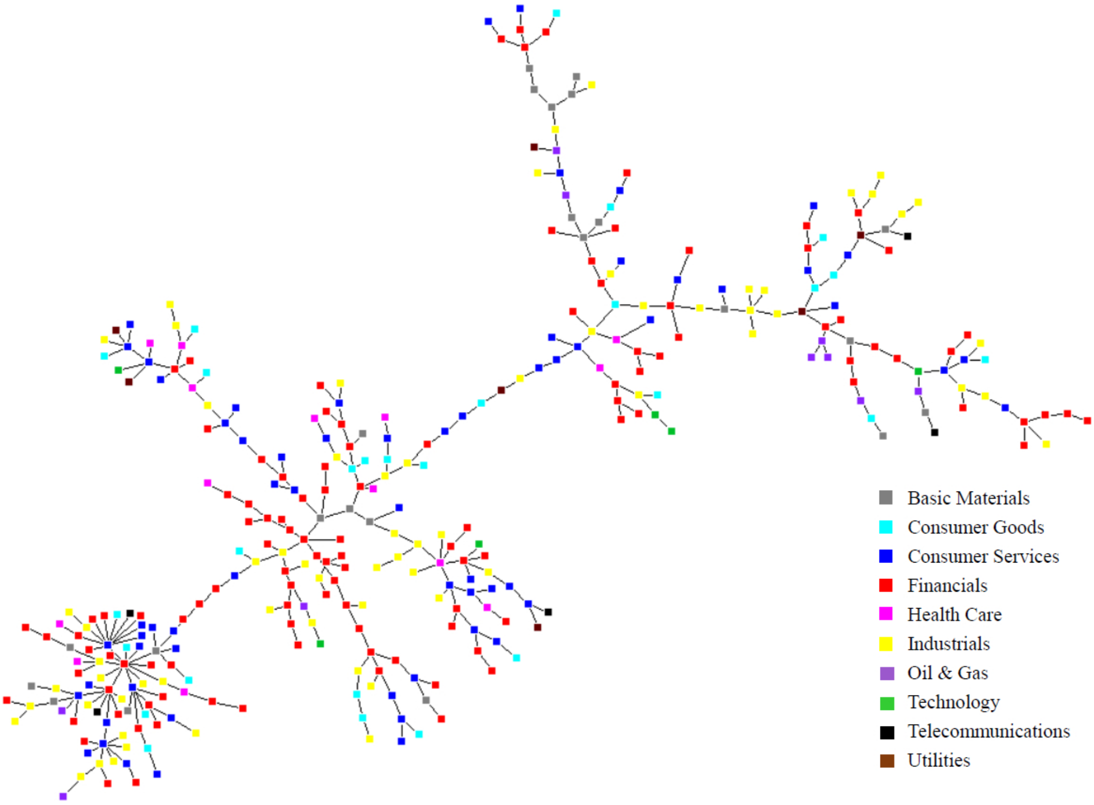
5.5 MSTs Analysis for the UK Stock Market pre- and post-Brexit

Since the resulting stock networks based on the ECM models are relatively complex (i.e., as shown in Fig. 5.2, there existing large number of incoming and outgoing linkages) even using the FDR with $\alpha = 0.01$ through the BH statistical validation tests. To enable the complexity reduction, the minimal spanning tree (MST) technique has been applied to filter significant information out of our constructed British stock networks.

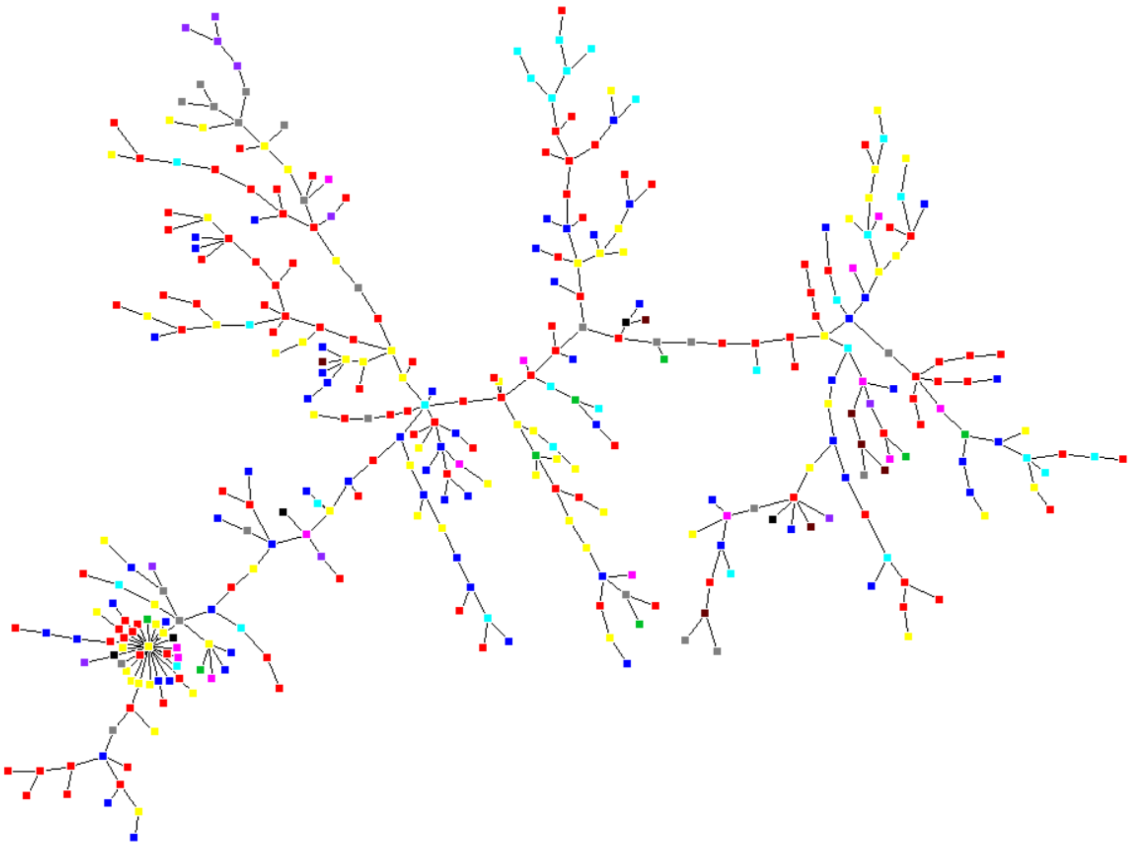
More specifically, the MST filter the network with the most strongly related connections (with $N-1$ links) in the stock network.

With respect to the MSTs extracted from Jaccard distance matrix based on in- and out-neighbors, highlighting the similar error correction behaviors of stocks in the UK stock market from a sectoral level. Specifically, structure changes will be studied by comparing the topological pattern of the MSTs before and after one-year of the Brexit. Fig. 5.3(a) and Fig. 5.3(b) respectively illustrate the MSTs of the UK stock network connecting 338 stocks for the period from 1 June 2015 to 22 June 2016 (before Brexit-vote). The Fig. 5.4(a) and Fig. 5.4(b) depict the structure information of the MSTs that connecting 348 British stocks after the Brexit vote (23 June 2016–30 June 2017). In addition, each stock in the MSTs is colored by its Industry Classification Benchmark (ICB): (Gray)–Basic Materials; (Cyan)–Consumer Goods; (Blue)–Consumer Services; (Red)–Financials; (Magenta)–Health Care; (Yellow)–Industrials; (Purple)–Oil & Gas; (PineGreen)–Technology; (Black)–Telecommunications; (Brown)–Utilities.

Fig. 5.3(a) and Fig. 5.3(b) displayed the structure information of MSTs before and after one-year of the Brexit-vote based on in-neighbor Jaccard distance matrix. The closer the stocks connected in the MSTs, the more common in-neighbors they have. Since the number of linkages (degree) is an important parameter in the MSTs, from Fig. 5.3(a), we can observe that the hubs which have more than three links in the MST are reported in Table. 5.3. By observing the Table. 5.3 and Fig. 5.3(a), there are 12 hubs from Financials, 10 hubs from Consumer Services, 4 hubs from Industrials, 3 hubs from Basic Materials, 2 hubs from Utilities, 1 hub from Health Care and 1 hub from Consumer Goods as cores of the MST before Brexit-vote. Particularly, the largest cluster with the center of stock from Financials in the MST is made up of a set of stocks from the industries of Financials (3), Industrials (4), Consumer Services (3), Consumer Goods (1), and Basic Materials (1), respectively. Besides, before Brexit-vote, the stocks from Financials, Industrials, Consumer Services as well as Basic Materials seem to be rather compact and cover a larger area than that aftermath of the Brexit-vote in the MST structure in Fig. 5.3(b). As expected, most of the stocks from the Utility, Telecommunications, Technology are located in the periphery of the MST.



(a) MST network based on Jaccard Distance (in-neighbors) before Brexit-vote (1/6/2015–22/6/2016)



(b) MST network based on Jaccard Distance (in-neighbors) after Brexit-vote (23/6/2016–30/6/2017)

Fig. 5.3. MSTs based on Jaccard Distance (in-neighbors) of the UK stock market.

Table 5.2. The hubs with degree greater than three in Fig. 5.3(a).

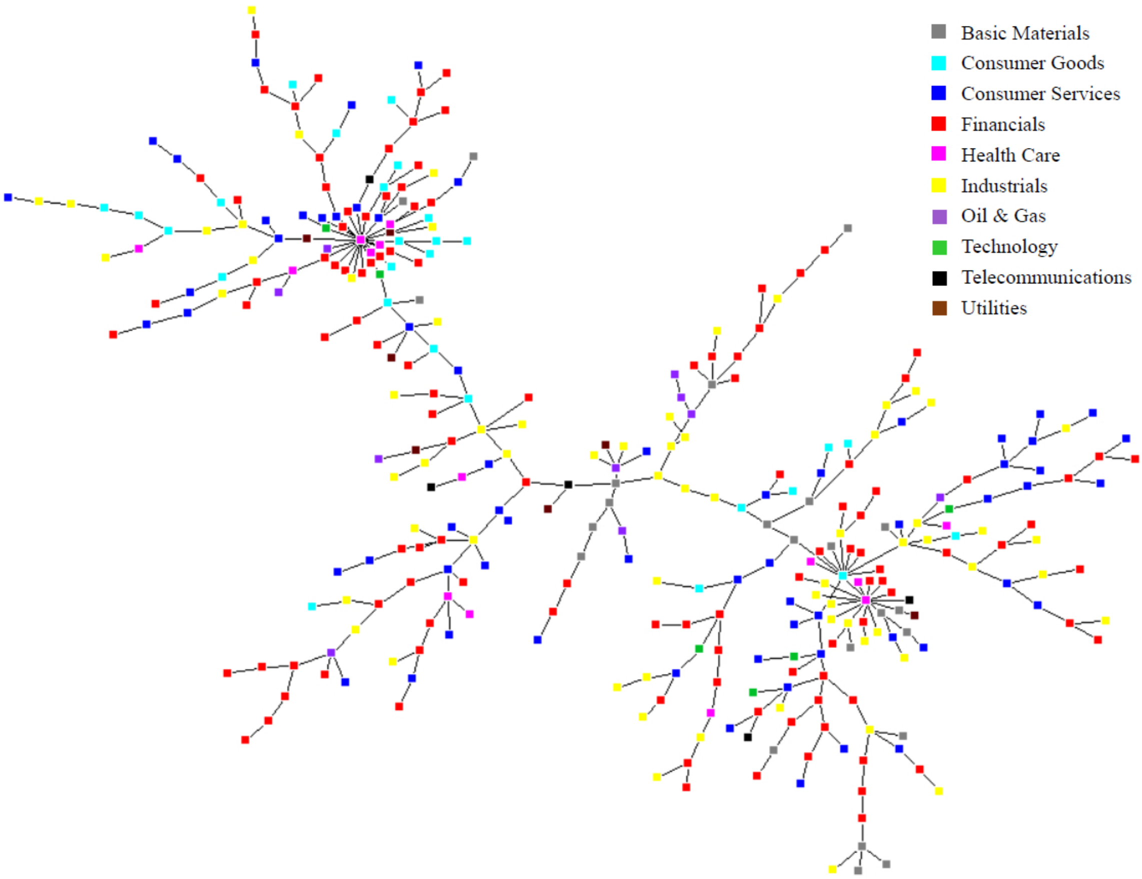
No.	Degree	Stock Name	ICBIN	ICBSN
279	12	REDEFINE INTL.REIT	Financials	Real Estate Investment Trusts
297	11	SPORTS DIRECT INTL.	Consumer Services	General Retailers
270	8	RANK GROUP	Consumer Services	Travel & Leisure
274	8	THE RENEWABLES INFR.GP.	Financials	Equity Investment Instruments
247	6	NMC HEALTH	Health Care	Health Care Equipment & Services
332	6	WIZZ AIR HOLDINGS	Consumer Services	Travel & Leisure
68	5	RIO TINTO	Basic Materials	Mining
109	5	ASSURA	Financials	Real Estate Investment Trusts
117	5	BBA AVIATION	Industrials	Industrial Transportation
134	5	CAPITAL & CNTS.PROPS.	Financials	Real Estate Investment & Services
152	5	DIGNITY	Consumer Services	General Retailers
193	5	HARBOURVEST GLOBAL	Financials	Equity Investment Instruments
215	5	JD SPORTS FASHION	Consumer Services	General Retailers
266	5	POLYMETAL INTERNATIONAL	Basic Materials	Mining
283	5	SAGA	Consumer Services	General Retailers
7	4	AVIVA	Financials	Life Insurance
14	4	BRITISH AMERICAN TOBACCO	Consumer Goods	Tobacco
27	4	DIRECT LINE IN.GROUP	Financials	Nonlife Insurance
40	4	ICTL.HTLS.GP.	Consumer Services	Travel & Leisure
57	4	NEXT	Consumer Services	General Retailers
64	4	RANDGOLD RESOURCES	Basic Materials	Mining
86	4	SSE	Utilities	Electricity
88	4	STANDARD CHARTERED	Financials	Banks
89	4	STANDARD LIFE	Financials	Life Insurance
133	4	CAPITA	Industrials	Support Services
138	4	CINEWORLD GROUP	Consumer Services	Travel & Leisure
156	4	DRAX GROUP	Utilities	Electricity
170	4	FIDELITY CHINA SPSTN.	Financials	Equity Investment Instruments
194	4	HAYS	Industrials	Support Services
236	4	MILLENNIUM & CPTH.HTLS.	Consumer Services	Travel & Leisure
242	4	MURRAY INTL.	Financials	Equity Investment Instruments
259	4	PERSONAL ASSETS	Financials	Equity Investment Instruments
284	4	SANNE GROUP	Industrials	Support Services

After the one-year of Brexit-vote, in Fig. 5.3(b), one can note that the hubs which have more than three degree in the MST are listed in Table. 5.4. There are 12 hubs from Financials, 9 hubs from Industrials, 6 hubs from Consumer Services, 3 hubs from Basic Materials, 3 hubs from Consumer Goods, 3 hubs from Health Care, and 1 hub from Technology, respectively. It is worth noting that the largest cluster in Fig. 5.3(b), the stock from Industrials assumes the role of the main hub for the tree with 27 connections with other stocks, replacing the Financials as the core in the Fig. 5.3(a) before Brexit-vote. To specify, this cluster with Industrials at its center, which is composed of 7 stocks from Industrials, 9 stocks from Financials, 3 stocks from Consumer Services, 2 stocks from Health Care, 2 stocks from Basics Materials, 2 stocks from Telecommunications, and 1 stocks from Technology, as well as 1 stock from Consumer Goods, respectively. Likewise, we also find that most of the stocks from Utilities are still located in the periphery of the MST aftermath of the Brexit-vote.

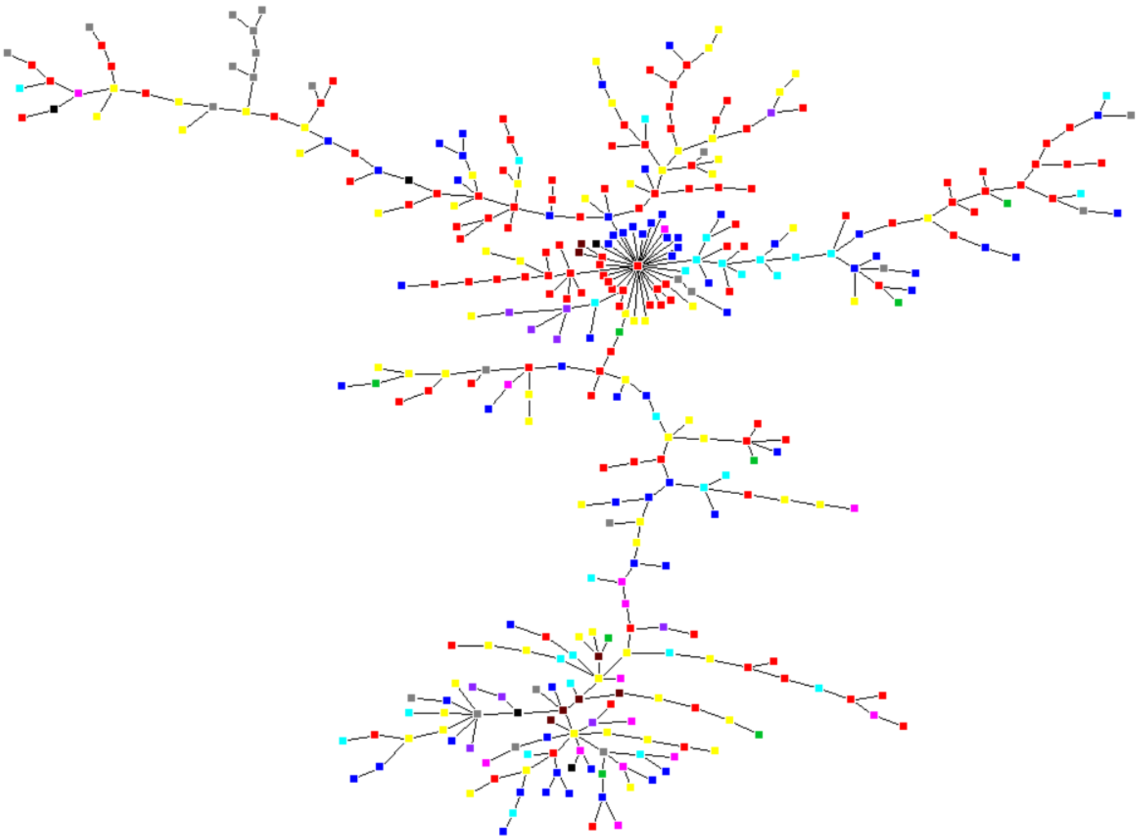
Table 5.3. The hubs with degree greater than three in Fig. 5.3(b).

No.	Degree	Stock Name	ICBIN	ICBSN
311	27	STOBART GROUP ORD.	Industrials	Industrial Transportation
18	6	BURBERRY GROUP	Consumer Goods	Personal Goods
218	6	IP GROUP	Financials	Financial Services (Sector)
7	5	AVIVA	Financials	Life Insurance
129	5	BREWIN DOLPHIN	Financials	Financial Services (Sector)
145	5	COATS GROUP	Industrials	General Industrials
177	5	FINSBURY GW.& INC.TST.	Financials	Equity Investment Instruments
189	5	GREENCOAT UK WIND	Financials	Equity Investment Instruments
273	5	POLAR CAPITAL TECH.TST.	Financials	Equity Investment Instruments
289	5	RPC GROUP	Industrials	General Industrials
300	5	SIRIUS MINERALS	Basic Materials	Mining
4	4	ASHTEAD GROUP	Industrials	Support Services
33	4	GLAXOSMITHKLINE	Health Care	Pharmaceuticals & Biotechnology
34	4	GLENCORE	Basic Materials	Mining
53	4	MICRO FOCUS INTL.	Technology	Software & Computer Services
65	4	RECKITT BENCKISER GROUP	Consumer Goods	Household Goods & Home Construction
66	4	RELX	Consumer Services	Media
67	4	RENTOKIL INITIAL	Industrials	Support Services
81	4	SHIRE	Health Care	Pharmaceuticals & Biotechnology
85	4	SMURFIT KAPPA GP. (LON)	Industrials	General Industrials
103	4	ABERFORTH SMCOS.	Financials	Equity Investment Instruments
117	4	BANKERS INV.TRUST	Financials	Equity Investment Instruments
118	4	BARR (AG)	Consumer Goods	Beverages
126	4	BODYCOTE	Industrials	Industrial Engineering
132	4	BTG	Health Care	Pharmaceuticals & Biotechnology
137	4	CARD FACTORY	Consumer Services	General Retailers
157	4	DIPLOMA	Industrials	Support Services
169	4	EUROMONEY INSTL.INVESTOR	Consumer Services	Media
197	4	HARBOURVEST GLOBAL	Financials	Equity Investment Instruments
228	4	JUST EAT	Consumer Services	General Retailers
230	4	KAZ MINERALS	Basic Materials	Mining
235	4	LONDONMETRIC PROPERTY	Financials	Real Estate Investment Trusts
246	4	MITIE GROUP	Industrials	Support Services
247	4	MONEYSUPERMARKET COM GP.	Consumer Services	Media
248	4	MONKS INV.TRUST	Financials	Equity Investment Instruments
262	4	PARAGON GP.OF COS.	Financials	Financial Services (Sector)
339	4	WH SMITH	Consumer Services	General Retailers

The results obtained from the MSTs in Fig. 5.3(a) and Fig. 5.3(b) based on the in-neighbor Jaccard distance are consistent with economic intuition that the economy of the UK is market-oriented, as more than 70% of Britain's economy is service industry, such as Banking, Insurance, and Real Estate, while Manufacturing and Health Care only account for 10% and 9.1% respectively. The closer distance in the MSTs of Fig. 5.3, highlighting that there are a large number of common stocks response their short-run deviations and restore the cointegral relationships with stocks from Financials and Consumer Services before Brexit-vote, as well as Industrials and Consumer Goods aftermath of the Brexit-vote.



(a) MST network based on Jaccard Distance (out-neighbors) before Brexit-vote (1/6/2015–22/6/2016)



(b) MST network based on Jaccard Distance (out-neighbors) after Brexit-vote (23/6/2016–30/6/2017)

Fig. 5.4. MSTs based on Jaccard Distance (in-neighbors) of the UK stock market.

When we examine the topologies structure of MSTs before and after one-year of the Brexit-vote based on out-neighbor Jaccard distance matrix in the Fig. 5.4(a) and Fig. 5.4(b), the closer the stocks connected, indicating more common out-neighbors they have. The hubs of MST before Brexit-vote in the Fig. 5.4(a) are summarized in Table. 5.4. There are 8 hubs from Consumer Services, 6 hubs from Industrials, 5 hubs from Financials, 3 hubs from Consumer Goods, 3 hubs from Basic Materials, 3 hubs from Health Care, and 2 hubs from Oil & Gas. It worth noting that for the MST based on out-Jaccard distance before Brexit-vote, one can note that two stocks from Health Care are denominated as the centers of the two largest clusters in the Fig. 5.4(a). Specifically, the former cluster (with degree=25) is composed of a set of stocks from the industries of Financials (10), Consumer Services (4), Health Care (3), Consumer Goods (2), Utility (2), Technology (2), Industrial (1) and Oil & Gas (1). The latter (with degree=15) which composed other stocks from Financials (4), Industrials (6), Basic Material (2), Health Care (1), Consumer Goods (1), as well as Telecommunications (1), respectively.

Then we turn to MST that based on out-neighbor Jaccard distance in Fig. 5.4(b), the presence of the hubs which have more than three degree in the MST are reported in Table. 5.5 after the Brexit-vote. From Fig. 5.4(b) and Table. 5.5, we can see that there are 19 stocks from Financials, 5 stocks from Consumer Goods, 2 stocks from Consumer Services, 5 stocks from Industrials, 3 stocks from Utilities, 2 stocks from Basic Materials, and 1 stock from Oil & Gas, respectively. In Fig. 5.4(b), conversely to what can been observed from the MST before Brexit-vote, the largest cluster (with degree=32) of stocks with the core of Financials in the MST after the Brexit-vote are distinctly assembled with the more stocks from Financials (12), Consumer services (12), Industrials (3), Consumer goods (2), Health Care (1), Basic Materials (1), Telecommunications (1), and Utility (1). The results which reflecting that stocks from industries of Health Care (before Brexit-vote) and Financials (after the Brexit-vote) have significant movement to respond to their short-run deviations and tend to restore the long-run equilibrium with common stocks after the shock in the system.

Table 5.4. The hubs with degree greater than three in Fig. 5.4(a).

No.	Degree	Stock Name	ICBIN	ICBSN
33	25	GLAXOSMITHKLINE	Health Care	Pharmaceuticals Biotechnology
196	15	HIKMA PHARMACEUTICALS	Health Care	Pharmaceuticals & Biotechnology
5	11	ASSOCIATED BRIT.FOODS	Consumer Goods	Food Producers
175	6	FISHER(JAMES)& SONS	Industrials	Industrial Transportation
166	5	EVRAZ	Basic Materials	Industrial Metals & Mining
202	5	HUNTING	Oil & Gas	Oil Equipment & Services
275	5	RENISHAW	Industrials	Electronic & Electrical Equipment
277	5	RIGHTMOVE	Consumer Services	Media
324	5	VESUVIUS	Industrials	General Industrials
4	4	ASHTEAD GROUP	Industrials	Support Services
17	4	BUNZL	Industrials	Support Services
30	4	FRESNILLO	Basic Materials	Mining
38	4	IMPERIAL BRANDS	Consumer Goods	Tobacco
43	4	ITV	Consumer Services	Media
81	4	SHIRE	Health Care	Pharmaceuticals & Biotechnology
89	4	STANDARD LIFE	Financials	Life Insurance
98	4	WPP	Consumer Services	Media
116	4	BARR (AG)	Consumer Goods	Beverages
125	4	BOOKER GROUP	Consumer Services	Food & Drug Retailers
138	4	CINEWORLD GROUP	Consumer Services	Travel & Leisure
151	4	DERWENT LONDON	Financials	Real Estate Investment Trusts
165	4	EUROMONEY INSTL.INVESTOR	Consumer Services	Media
169	4	FERREXPO	Basic Materials	Industrial Metals & Mining
209	4	INTERNATIONAL PBPART.	Financials	Equity Investment Instruments
227	4	LADBROKES CORAL GROUP	Consumer Services	Travel & Leisure
236	4	MILLENNIUM & CPTH.HTLS.	Consumer Services	Travel & Leisure
249	4	NOSTRUM OIL & GAS	Oil & Gas	Oil & Gas Producers
295	4	SPIRAX-SARCO ENGR.	Industrials	Industrial Engineering
309	4	TEMPLE BAR	Financials	Equity Investment Instruments
331	4	WITAN INV.TRUST	Financials	Equity Investment Instruments

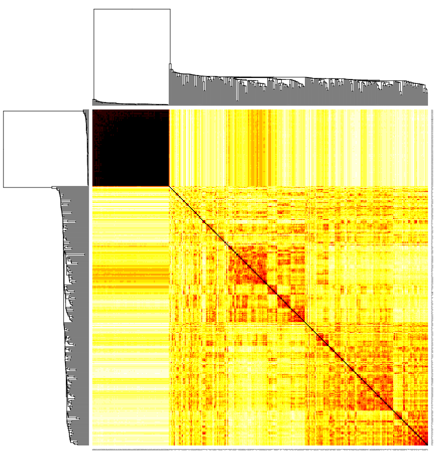
Table 5.5. The hubs with degree greater than three in Fig. 5.4(b).

No.	Degree	Stock Name	ICBIN	ICBSN
27	32	DIRECT LINE IN.GROUP	Financials	Nonlife Insurance
122	8	BERENDSEN	Industrials	Support Services
268	7	PETRA DIAMONDS	Basic Materials	Mining
17	6	BUNZL	Industrials	Support Services
35	6	HAMMERSON	Financials	Real Estate Investment Trusts
7	5	AVIVA	Financials	Life Insurance
11	5	BARRATT DEVELOPMENTS	Consumer Goods	Household Goods & Home Construction
94	5	UNITED UTILITIES GROUP	Utilities	Gas, Water & Multiutilities
113	5	AUTO TRADER GROUP	Consumer Services	Media
128	5	BOVIS HOMES GROUP	Consumer Goods	Household Goods & Home Construction
192	5	GREGGS	Consumer Services	Food & Drug Retailers
196	5	HANSTEEN HOLDINGS	Financials	Real Estate Investment Trusts
259	5	ONESAVINGS BANK	Financials	Financial Services (Sector)
286	5	RIT CAPITAL PARTNERS	Financials	Equity Investment Instruments
14	4	BRITISH AMERICAN TOBACCO	Consumer Goods	Tobacco
62	4	PROVIDENT FINANCIAL	Financials	Financial Services (Sector)
67	4	RENTOKIL INITIAL	Industrials	Support Services
72	4	ROYAL DUTCH SHELL B	Oil & Gas	Oil & Gas Producers
80	4	SEVERN TRENT	Utilities	Gas, Water & Multiutilities
90	4	TAYLOR WIMPEY	Consumer Goods	Household Goods & Home Construction
123	4	BERKELEY GROUP HDG.(THE)	Consumer Goods	Household Goods & Home Construction
157	4	DIPLOMA	Industrials	Support Services
183	4	GENESIS EMRG.MKTS.	Financials	Equity Investment Instruments
187	4	GRAINGER	Financials	Real Estate Investment & Services
217	4	INVESTEC	Financials	Financial Services (Sector)
224	4	JPMORGAN AMERICAN IT.	Financials	Equity Investment Instruments
254	4	NEX GROUP	Financials	Financial Services (Sector)
265	4	PENNON GROUP	Utilities	Gas, Water & Multiutilities
290	4	SAFESTORE HOLDINGS	Financials	Real Estate Investment Trusts
292	4	SANNE GROUP	Industrials	Support Services
300	4	SIRIUS MINERALS	Basic Materials	Mining
323	4	TR PROPERTY INV.	Financials	Equity Investment Instruments

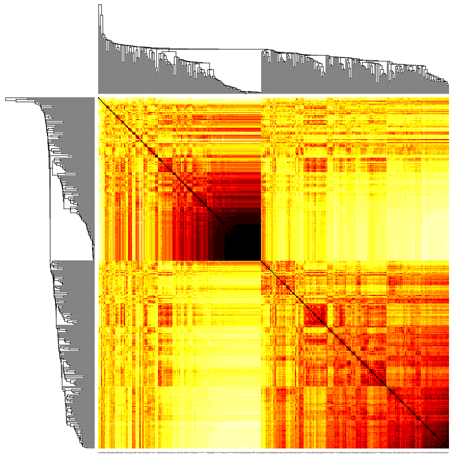
5.6 Hierarchical Clustering Analysis of the UK Stock Market pre- and post-Brexit

Since stocks in the community might share common properties or attributes in the stock market, in this section, regarding the network community detection in the British stock market, we employ the hierarchical clustering algorithm. In Fig. 5.5–Fig. 5.7, the dendrograms with the corresponding heatmaps are generated with the complete, average and single linkage agglomerative hierarchical clustering algorithm based on both in- and out-neighbor Jaccard distance matrix respectively. The dendrogram from Fig. 5.5 to Fig. 5.7 is added on top and side that is created with a corresponding hierarchical clustering algorithm, then the heatmap automatically reorders the nodes to cluster them effectively. Additional, the colors in each heatmap will then be assigned to the distance matrix to represent the Jaccard distance value, and the darker the lattice, the closer the Jaccard distance between each pair of stocks in the British stock market.

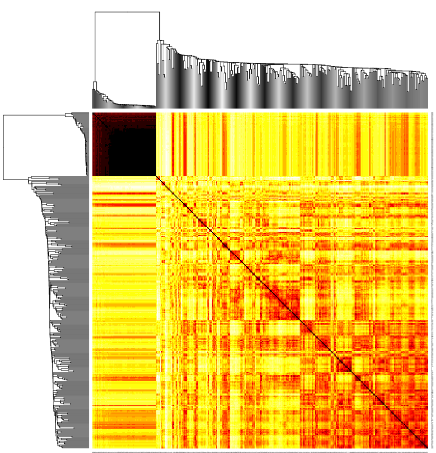
From Fig. 5.5 to Fig. 5.7, the hierarchical structure of the stocks listed on FTSE 100 and FTSE Mid250 index demonstrate that the existence of various hierarchy clusters in the British stock market pre- or post-Brexit. To specify, the hierarchical organization is the existence of a nested block diagonal structure with the darker color in both in- and out-neighbor Jaccard distance matrix in corresponding heatmaps. Here, by comparing the size of the hierarchical clusters before and after the Brexit-vote, the larger hierarchical organizations appear after the period of post-Brexit based on both in- and out-neighbor Jaccard distance, respectively. This finding provides evident proof of stocks' homogeneous tendency associated with the impact of the Brexit-vote, which made stocks contained in same community would behave similarly in the British stock market.



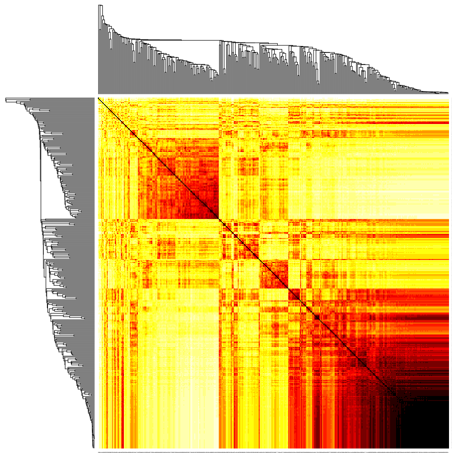
(a) Before Brexit-vote (based on in-neighbors)



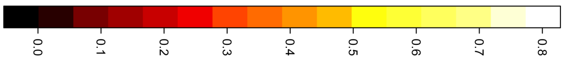
(b) Before Brexit-vote (based on out-neighbors)



(c) After Brexit-vote (based on in-neighbors)

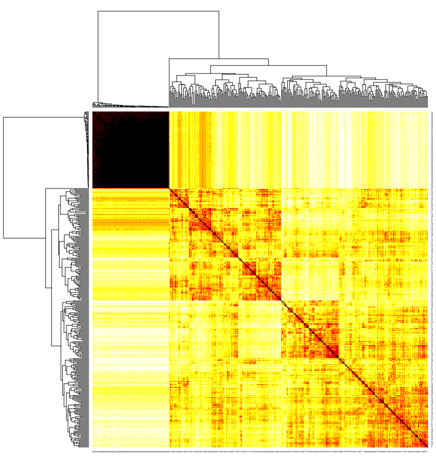


(d) After Brexit-vote (based on out-neighbors)

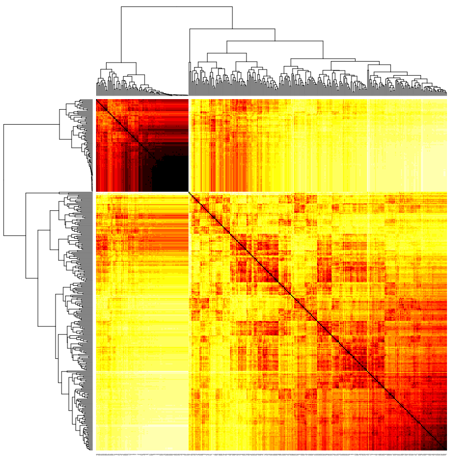


(e)

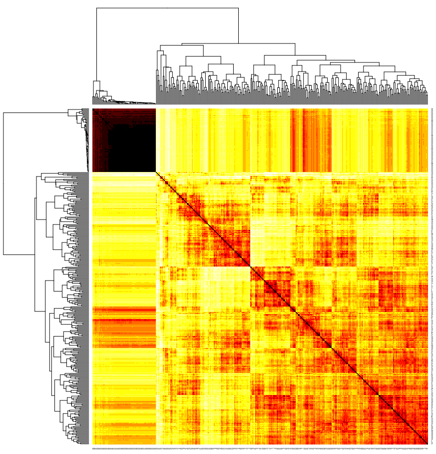
Fig. 5.5. Heatmap visualization of hierarchical clustering based on single linkage. Dark red (blue) regions shows closer (farer) distance.



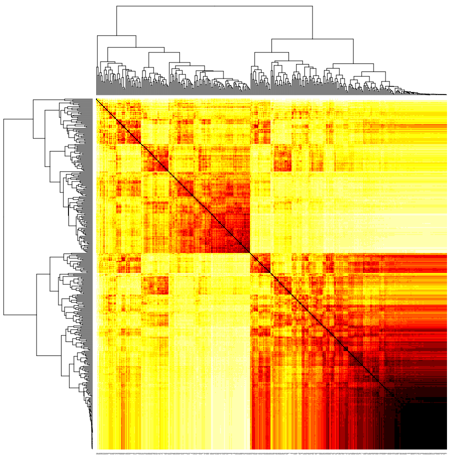
(a) Before Brexit-vote (based on in-neighbors)



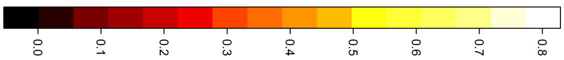
(b) Before Brexit-vote (based on out-neighbors)



(c) After Brexit-vote (based on in-neighbors)

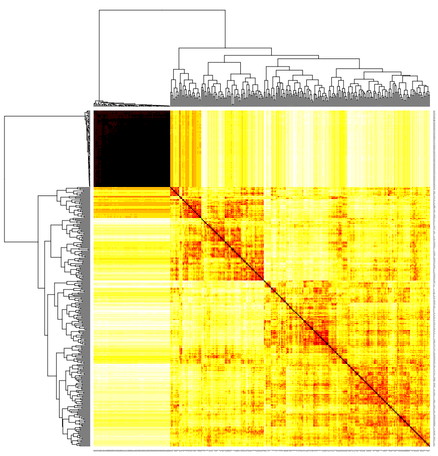


(d) After Brexit-vote (based on out-neighbors)

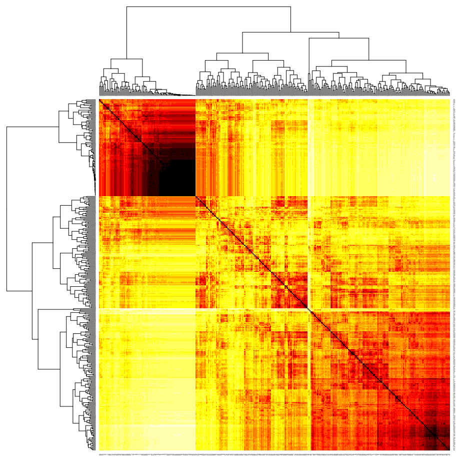


(e)

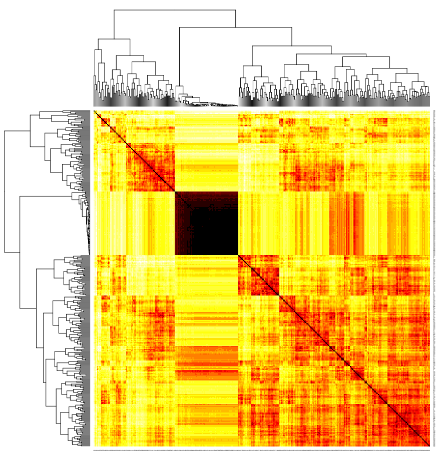
Fig. 5.6. Heatmap visualization of hierarchical clustering based on average linkage. Dark red (blue) regions shows closer (farer) distance.



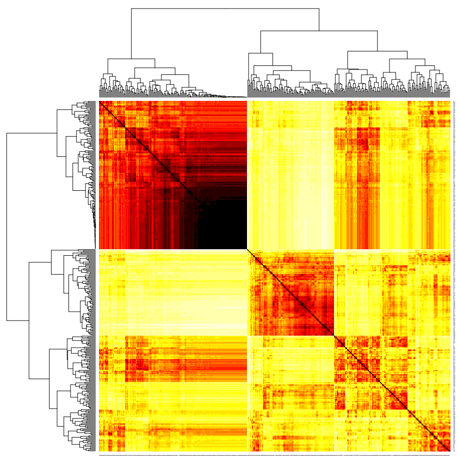
(a) Before Brexit-vote (based on in-neighbors)



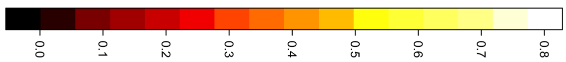
(b) Before Brexit-vote (based on out-neighbors)



(c) After Brexit-vote (based on in-neighbors)



(d) After Brexit-vote (based on out-neighbors)



(e)

Fig. 5.7. Heatmap visualization of hierarchical clustering based on complete linkage. Dark red (blue) regions shows closer (farer) distance.

Table 5.6. The largest community based on average linkage clustering algorithm in Fig. 5.6(b)

No.	Stock Name	ICBIN	ICBSN
139	CITY OF LONDON IT.	Financials	Equity Investment Instruments
158	EDINBURGH INV.TRUST	Financials	Equity Investment Instruments
171	FIDELITY EUR.VALUES	Financials	Equity Investment Instruments
173	FINSBURY GW.& INC.TST.	Financials	Equity Investment Instruments
176	FOREIGN & COLONIAL	Financials	Equity Investment Instruments
278	RIT CAPITAL PARTNERS	Financials	Equity Investment Instruments
303	SYNCONA	Financials	Equity Investment Instruments
313	TR PROPERTY INV.	Financials	Equity Investment Instruments
331	WITAN INV.TRUST	Financials	Equity Investment Instruments
49	LONDON STOCK EX.GROUP	Financials	Financial Services (Sector)
203	IG GROUP HOLDINGS	Financials	Financial Services (Sector)
312	TP ICAP	Financials	Financial Services (Sector)
142	CLS HOLDINGS	Financials	Real Estate Investment & Services
148	DAEJAN HOLDINGS	Financials	Real Estate Investment & Services
79	SEGRO	Financials	Real Estate Investment Trusts
109	ASSURA	Financials	Real Estate Investment Trusts
229	LONDONMETRIC PROPERTY	Financials	Real Estate Investment Trusts
245	NEWRIVER REIT (REG S)	Financials	Real Estate Investment Trusts
1	ADMIRAL GROUP	Financials	Nonlife Insurance
87	ST.JAMES'S PLACE	Financials	Life Insurance
11	BARRATT DEVELOPMENTS	Consumer Goods	Household Goods & Home Construction
61	PERSIMMON	Consumer Goods	Household Goods & Home Construction
65	RECKITT BENCKISER GROUP	Consumer Goods	Household Goods & Home Construction
90	TAYLOR WIMPEY	Consumer Goods	Household Goods & Home Construction
119	BELLWAY	Consumer Goods	Household Goods & Home Construction
121	BERKELEY GROUP HDG.(THE)	Consumer Goods	Household Goods & Home Construction
147	CREST NICHOLSON HOLDINGS	Consumer Goods	Household Goods & Home Construction
26	DIAGEO	Consumer Goods	Beverages
129	BRITVIC	Consumer Goods	Beverages
38	IMPERIAL BRANDS	Consumer Goods	Tobacco
39	INFORMA	Consumer Services	Media
66	RELX	Consumer Services	Media
98	WPP	Consumer Services	Media
165	EUROMONEY INSTL.INVESTOR	Consumer Services	Media
19	CARNIVAL	Consumer Services	Travel & Leisure
22	COMPASS GROUP	Consumer Services	Travel & Leisure
332	WIZZ AIR HOLDINGS	Consumer Services	Travel & Leisure
157	DUNELM GROUP	Consumer Services	General Retailers
262	PETS AT HOME GROUP	Consumer Services	General Retailers
283	SAGA	Consumer Services	General Retailers
17	BUNZL	Industrials	Support Services
42	INTERTEK GROUP	Industrials	Support Services
23	CRH	Industrials	Construction & Materials
226	KIER GROUP	Industrials	Construction & Materials
293	SMITH (DS)	Industrials	General Industrials
9	BAE SYSTEMS	Industrials	Aerospace & Defense
6	ASTRAZENECA	Health Care	Pharmaceuticals & Biotechnology
33	GLAXOSMITHKLINE	Health Care	Pharmaceuticals & Biotechnology
180	GENUS	Health Care	Pharmaceuticals & Biotechnology
322	VECTURA GROUP	Health Care	Pharmaceuticals & Biotechnology
75	SAGE GROUP	Technology	Software & Computer Services
145	COMPUTACENTER	Technology	Software & Computer Services
24	CRODA INTERNATIONAL	Basic Materials	Chemicals
161	ELEMENTIS	Basic Materials	Chemicals
56	NATIONAL GRID	Utilities	Gas, Water & Multiutilities
80	SEVERN TRENT	Utilities	Gas, Water & Multiutilities
95	VODAFONE GROUP	Telecommunications	Mobile Telecommunications
333	WOOD GROUP (JOHN)	Oil & Gas	Oil Equipment & Services

To concentrate on the short-run error adjustment effects of British stocks back to their long-run equilibrium state, we only report the largest hierarchical organization (i.e., community) that extract from the Jaccard distance matrix based on the out-neighbors before and after the Brexit-vote in Table. 5.6 and Table. **??**, respectively. Since more common out-neighbors they have, the closer distance between the stocks and would contained in the same community, indicating that they all respond to their disequilibrium and restore the long-run equilibrium with common stocks in the British market. Table. 5.6 lists stocks that observing from Fig. 5.6(b). The results reveal that stocks belonging to the Financials (20), Consumer Goods (10), Consumer Services (10), Industrials (6), Health Care (4), Technology (2), Basic Materials (2), Utilities (2), Telecommunications (1) and Oil & Gas (1) are clustered in same hierarchical organization with total number of 58 stocks before one-year of Brexit vote.

However, after one-year of the Brexit-vote, the size of the largest community that extracts from Jaccard distance matrix based on the out-neighbors is greater than that before Brexit-vote. The corresponding members of this community reported in Table. **??** reveal that the stocks have similar behaviors that they all respond to their disequilibrium and restore the long-run equilibrium with common stocks in the UK stock market. This largest community with total number of 62 stocks, which is composed by the Financials (28), Consumer Services (15), Consumer Goods (9), Industrials (5), Technology (1), Utilities (1), Telecommunications (1), Basic Materials (1), and Health Care (1) after one-year of Brexit. It is worth noting that one significant difference compared to pre-Brexit-vote period is that the economic sectors of Banks are identified to be contained in the largest community with other economic sectors. Further, after the Brexit-vote, there are more stocks from the sectors of Real Estate Investment & Services, Real Estate Investment Trusts, Household Goods & Home Construction, General Retailers as well as Travel & Leisure, which share common out-neighbors in the British stock market. In other words, these sectors significantly response to their disequilibrium and restore the long-run equilibrium with common stocks after the shock of Brexit vote.

Table 5.7. The largest community based on average linkage clustering algorithm in Fig. 5.6(d)

No.	Stock Name	ICBIN	ICBSN
48	LLOYDS BANKING GROUP	Financials	Banks
70	ROYAL BANK OF SCTL.GP.	Financials	Banks
151	CYBG	Financials	Banks
298	SHAWBROOK GROUP	Financials	Banks
336	VIRGIN MONEY HOLDINGS	Financials	Banks
189	GREENCOAT UK WIND	Financials	Equity Investment Instruments
215	INTERNATIONAL PBPART.	Financials	Equity Investment Instruments
344	WOODFORD PTNT.CAP.TST.	Financials	Equity Investment Instruments
348	3I INFRASTRUCTURE	Financials	Equity Investment Instruments
136	CAPITAL & CNTS.PROPS.	Financials	Real Estate Investment & Services
144	CLS HOLDINGS	Financials	Real Estate Investment & Services
152	DAEJAN HOLDINGS	Financials	Real Estate Investment & Services

Continued on next page

Table 5.7 – *Continued from previous page*

No.	Stock Name	ICBIN	ICBSN
187	GRAINGER	Financials	Real Estate Investment & Services
309	ST MODWEN PROPS.	Financials	Real Estate Investment & Services
329	UK COMMERCIAL PR.TST.	Financials	Real Estate Investment & Services
15	BRITISH LAND	Financials	Real Estate Investment Trusts
35	HAMMERSON	Financials	Real Estate Investment Trusts
46	LAND SECURITIES GROUP	Financials	Real Estate Investment Trusts
111	ASSURA	Financials	Real Estate Investment Trusts
155	DERWENT LONDON	Financials	Real Estate Investment Trusts
188	GREAT PORTLAND ESTATES	Financials	Real Estate Investment Trusts
216	INTU PROPERTIES	Financials	Real Estate Investment Trusts
253	NEWRIVER REIT (REG S)	Financials	Real Estate Investment Trusts
325	TRITAX BIG BOX REIT	Financials	Real Estate Investment Trusts
36	HARGREAVES LANSDOWN	Financials	Financial Services (Sector)
47	LEGAL & GENERAL	Financials	Life Insurance
271	PHOENIX GROUP HDG.	Financials	Life Insurance
27	DIRECT LINE IN.GROUP	Financials	Nonlife Insurance
76	SAINSBURY (J)	Consumer Services	Food & Drug Retailers
50	MARKS & SPENCER GROUP	Consumer Services	General Retailers
156	DIGNITY	Consumer Services	General Retailers
158	DIXONS CARPHONE	Consumer Services	General Retailers
194	HALFORDS GROUP	Consumer Services	General Retailers
307	SPORTS DIRECT INTL.	Consumer Services	General Retailers
339	WH SMITH	Consumer Services	General Retailers
59	PADDY POWER BETFAIR(LON)	Consumer Services	Travel & Leisure
92	TUI (LON)	Consumer Services	Travel & Leisure
244	MILLENNIUM & CPTH.HTLS.	Consumer Services	Travel & Leisure
310	STAGECOACH GROUP	Consumer Services	Travel & Leisure
39	INFORMA	Consumer Services	Media
113	AUTO TRADER GROUP	Consumer Services	Media
169	EUROMONEY INSTL.INVESTOR	Consumer Services	Media
285	RIGHTMOVE	Consumer Services	Media
11	BARRATT DEVELOPMENTS	Consumer Goods	Household Goods & Home Construction
61	PERSIMMON	Consumer Goods	Household Goods & Home Construction
90	TAYLOR WIMPEY	Consumer Goods	Household Goods & Home Construction
121	BELLWAY	Consumer Goods	Household Goods & Home Construction
123	BERKELEY GROUP HDG.(THE)	Consumer Goods	Household Goods & Home Construction
128	BOVIS HOMES GROUP	Consumer Goods	Household Goods & Home Construction
150	CREST NICHOLSON HOLDINGS	Consumer Goods	Household Goods & Home Construction
239	MCCARTHY AND STONE	Consumer Goods	Household Goods & Home Construction
312	SUPERGROUP	Consumer Goods	Personal Goods
167	ESSENTRA PLC	Industrials	Support Services
263	PAYPOINT	Industrials	Support Services
324	TRAVIS PERKINS	Industrials	Support Services
208	IBSTOCK	Industrials	Construction & Materials
179	FISHER(JAMES)& SONS	Industrials	Industrial Transportation
114	AVEVA GROUP	Technology	Software & Computer Services
86	SSE	Utilities	Electricity
16	BT GROUP	Telecommunications	Fixed Line Telecommunications
204	HOCHSCHILD MINING	Basic Materials	Mining
212	INDIVIOR	Health Care	Pharmaceuticals & Biotechnology

To sum up, the results from the hierarchical clustering analysis of the British stock market based on our proposed Jaccard distance (both in- and out-neighbors) suggest that the significant changes in the response of the UK's EU membership referendum. Stocks traded on London Stock Exchange appear to behave more similar when facing the risk and uncertainty in the economic system of the UK. More stocks belonging to the Financials, Consumer Services, Consumer Goods, Industrials located in the largest hierarchical organization during the periods of both pre- and post-Brexit. Furthermore, there are more stocks from sectors of Chemicals, Oil Equipment & Services as well as Gas, Water & Multiutilities share common features with other important sectors in the community before the Brexit-vote. These findings associated with the financial market experienced recession fears in January 2016 following the great Chinese currency deterioration, as well as the market turmoil as oil price plunge attaining $25 a barrel, which caused the corresponding industry of Oil & Gas response significantly to adjust after the shocks in the system. However, one notable finding after the Brexit-vote is that the economic sector of Banks experienced dramatically short-run adjustment to its disequilibrium in the British stock market. The reason behinds the results is that the withdrawal from the European Union would end passporting rights, making the British operations of European Economic Area (EEA) banks and European operations of UK banks heavily harder to pursue. Besides, the economic sectors of Real Estate (i.e., Real Estate Investment & Services, and Real Estate Investment Trusts) also faced challenges with the Brexit-vote, which is significantly influenced by the UK referendum can be identified through the increasing stocks belonging to the corresponding sectors of Real Estate Investment & Services and Real Estate Investment Trusts in the largest community.

5.7 Conclusions

In this chapter, we concentrate on stocks appearing in FTSE 100 and FTSE Mid250 index to construct the corresponding financial networks based on error correction model (ECM) to study short-run adjustment effects and long-run cointegration amongst stocks from July 2007 to June 2017. Particularly, to investigate the financial effects of Brexit-vote on the network topological structure, we constructed corresponding British stock networks before and after one-year of the Brexit-vote. Further, to filter the ECM-based British stock network and detect the most strongly related stocks, the minimal spanning tree (MST) has been used based on our proposed Jaccard distance metric. Finally, the hierarchal clustering analysis is conducted to discover the similar behaviors and properties among the stocks in the UK stock market.

The findings of the ECM-based stock network in the sectoral-level over the entire sample period from July 2007 to June 2017, indicating that the Financials, Consumer Goods, Consumer Services have more significant adjustment effects to maintain the steady equilibrium state compared to the Industrials, Basic Materials, Utilities, and

Telecommunications. The evidence of the topological structure changes in MSTs before and after the Brexit-vote suggests that the most of the stocks from Financials, Consumer Goods, Consumer Services, Industrials located in the center of the MSTs, while the stocks from Utilities, Technology, and Telecommunications located in the periphery of the MSTs. Finally, the results of the community detection highlight the significant response of British stocks when facing the risk and uncertainty in the economic system of the UK. Especially, the stocks belonging to the sectors of Banks, Real Estate (Real Estate Investment & Services, and Real Estate Investment Trusts) appear to behave more similar after the Brexit-vote.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

This thesis investigates complex heterogeneous behaviors in the financial market by applying and developing the complex network theory and econometric measures from the time-varying perspective. The questions that this thesis intends to answer originate mainly from the economic, financial and political shocks lead to dramatic changes in investment behaviors, market fundamental and economic policies worldwide. Further, since there is a considerable number of heterogeneous interacting agents have been identified in the financial market, leading to complex interactions influencing the behavior of the financial market. Therefore, it is essential to consider the financial market as a Complex System to study the interaction patterns during periods of financial turmoil.

Moreover, due to the recognition of the non-stationarity of financial asset prices led to the exploration of possible long-run relations among asset prices using the framework of cointegration and error correction models to avoid the spurious relationship. In this thesis, the combination of the econometric measures (i.e., the cointegration technique and error correction models) and complex network theory could provide us a better way to capture the short-run error correction mechanisms as well as the long-run equilibrium amongst financial asset prices, especially, during the impacts of economic, financial, and political uncertainty periods.

It should be noted that the resulting financial networks based on ECM models in this thesis are usually relatively complex even after the statistical validation tests with the FDR $\alpha = 0.01$. In order to reduce the complexity of the ECM-based financial networks, the minimal spanning tree (MST) is employed for network filtering and to extract the most critical connections [6]. As it is well known that to analyze the topological MST network structure of the financial market, a distance metric is needed to define. Here, another distance metric, the Jaccard similarity of distance that evaluated from the constructed directed and weighted ECM-based financial networks is proposed in this thesis.

6.2 Key Recommendations

This thesis contains three research chapters preceded by a general introduction. Chapter 3 focuses on the dynamic analysis in terms of the evolution of short-term correlation, long-term cointegration and ECM-based long-term Granger causality between each pair of US (S&P 500), UK (FTSE 100), and Eurozone (EURO STOXX 50) stock markets over the period of 1980–2015 by using the rolling-window technique. In particular, a comparative analysis of pairwise dynamic integration and causality of stock markets, measured in common and domestic currency terms, is conducted to evaluate comprehensively how exchange rate fluctuations affect the time-varying integration among the S&P 500, FTSE 100 and EURO STOXX 50 indices.

Chapter 4 aims to incorporate the long-run cointegration and short-run error correction mechanisms to build up the financial networks for quantifying the interactions across 46 stock markets worldwide from January 2007 to June 2017. By building the static global stock market network, the topological structure clearly reflects the regional market integration and segment. The constructed dynamic international stock market networks further depict the time-varying properties of both error correction effect and long-run equilibrium relations amongst 46 stock markets worldwide during periods of financial turmoils and implementation of the QEs in the Fed, BoE, BoJ, and ECB, respectively. Especially, the network metrics are used to observe the time-varying structure of the dynamic world stock markets. Finally, to provide a better understanding of how financial turmoils, and the periods that QEs implementation is transmitted across markets, the potential differences and/or similarities in dynamic equilibrium self-adjustment effects of the stock markets of US, UK, Japan, and "PIIGS" countries, are re-investigated.

In Chapter 5, we have turned our attention to the financial effects of Brexit-vote on the stocks from the London Stock Exchange (FTSE 100 and FTSE Mid250 Index). Specifically, we construct corresponding British stock networks using the ECM models to investigate the short-run self-correction mechanism as well as long-run equilibrium amongst stocks in sector-level. To extract as strongly related interactions from the ECM-based stock networks, the minimal spanning tree (MST) and hierarchical cluster analysis are applied for filtering and to detect the taxonomy and hierarchical topological structure based our new proposed Jaccard distance metric.

6.3 Future Work

As indicated in the previous chapters, there are many unresolved topics within the context of this thesis.

In this thesis, the use of the rolling window technique to construct our ECM-based financial networks may obtain multifarious results due to researchers' specific option of parameters, namely the length and drift of the estimation window. Therefore, to undermine the objectivity and reasonability of the research conclusions to some extent.

Further, in Chapter 5, we only focus on the static British stock market network. Although the changes of topological structure could be observed through the sub-periods of pre- and post-Brexit, while the time-varying network structure would help us capture more characteristics from the ECM-based financial network. In addition, the application of our proposed ECM-based financial networks to guide the investment in the stock market is a critical research plan in the future. Especially, extensions of the Chapter 5, a novel investment decision strategy based on network structure could be detected further. Since the performance of many investment strategies is affected by portfolio similarity, we aim to provide two portfolio selection strategies based on time-varying MSTs and community structure in the British stock market, respectively. The first portfolio strategy comprises two stages: selecting the portfolios by choosing central and peripheral stocks in the selection horizon, then using the portfolios for investment in the investment horizon. The second portfolio investment strategy is to select the best Sharp ratio stock in each cluster in the investment horizon. Lastly, the outperform of the proposed portfolio strategies would be compared to the random strategy.

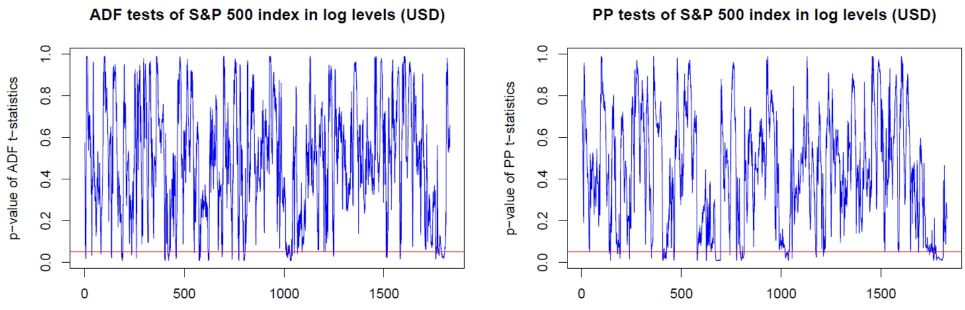
Appendix A

A.1 List of Shocks from 1980–2017

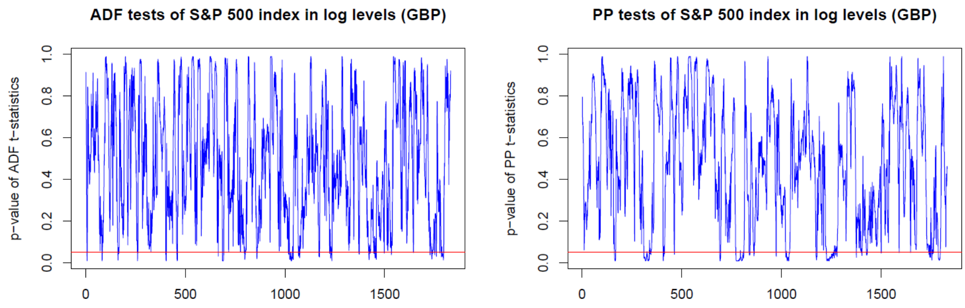
Table A.1. List of economic, financial and political shocks over 1980–2015.

Period	Name of the shocks	Date
1	Early 1980s recession in the UK	January 1st, 1980–March 31st, 1981
2	Early 1980s recession in the US	July 1981–November 1982
3	1982 Latin American debt crisis	August 1982
4	Economic recovery of the US and UK	From December 1982
5	1984–85 UK miners' strike	March 5th, 1984–May 3rd, 1985
6	Beginning of the US saving & loan crisis	March 5th, 1985
7	1985–87 US economic crisis after Palza Accord	December 22nd, 1985–1987
8	1987 Lawson Boom in the UK	March 1987
9	1987 "Black Monday" stock market crash	October 17th, 1987
10	1989 mini-crash of stock market	October 13th, 1989
11	1990 Japanese asset bubble collapse	December 29th, 1989
12	1990 Gulf War	August 2nd, 1990–February 28th, 1991
13	Early-1990s recession in the US & UK	July 1990–March 1991, US (July 1990–September 1991, UK)
14	1991 European Union established	December 31st, 1991
15	1992 "Black Wednesday" in the UK	September 16th, 1992
16	1992–93 European currency crisis	January 1st, 1993
17	1994 Mexico peso crisis	December 20th, 1994
18	1995-96 US government shut-down	November 13th, 1995–January 6th, 1996
19	1997 Asian financial crisis	July 2nd, 1997
21	1998 Russian financial crisis	August 17th, 1998
22	1999 Euro introduced	January 1st, 1999
23	1999 Kosovo War	March 24th, 1999
24	2000 bursting of dot-com bubble	March 10th, 2000
25	2001 Turkish economic crisis	February 19th, 2001
26	Early-2000s recession in the US	March 2001
27	9/11 Attacks	September 11th, 2001
28	2001 US war in Afghanistan	October 7th, 2001
29	2002 stock market downturn	October 9th, 2002
30	2003 US war in Iraq	March 20th, 2003
31	Beginning of US housing bubble of 2004–06	February 2004
32	Collapse of US housing bubble in mid-2006	June 2006
33	Origin of 2007 sub-prime mortgage crisis	April 2nd, 2007
34	US recession of Dec 2007–Jun 2009	December 2007
35	2008 Lehman Brothers collapse	September 16th, 2008
36	US QE1 announced	November 25th, 2008–March 31th, 2010
37	UK QE1 announced	March 5th, 2009–February 4th 2010
38	US QE1 extension	March 18th, 2009
39	2009 Dubai debt standstill	November 27th, 2009
40	2010 European sovereign debt crisis	April 27th, 2010
41	US QE2 announced	November 3th, 2010–June 3th, 2011
42	2011 Stock Market Fall	August 1st, 2011
43	US Operation Twist announced	September 11th, 2011–September 13th 2012
44	UK QE2 announced	October 6th, 2011–May 10th, 2012
45	UK QE3 announced	July 5th, 2012–November 5th, 2012
46	US QE3 announced	September 13th, 2012–October 31th, 2014
47	US QE3 extended & Operation Twist ends	December 12th, 2012
48	US QE3 taper announced	December 18th, 2013
49	2013 US debt-ceiling crisis	January 1st, 2013
50	2014 Russian financial crisis	December 16th, 2014
51	EU QE announced	January 22nd, 2015–present
52	201516 Chinese stock market turbulence	June 12th, 2015
53	2015–16 US stock market selloff	August 15th, 2015

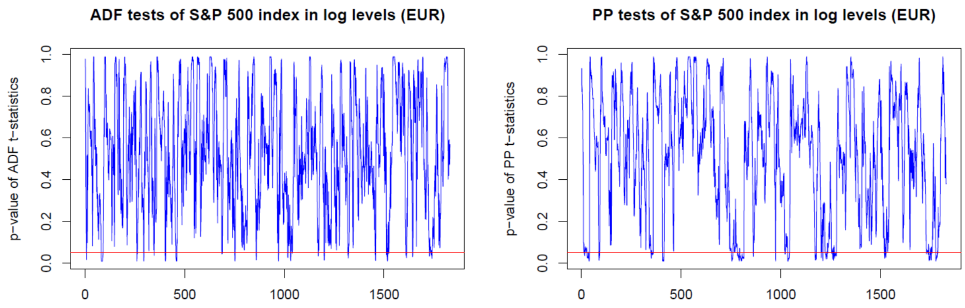
A.2 Unit Root Tests for S&P 500, FTSE 100 and EURO STOXX 50



(a) S&P 500 index in log level (USD)

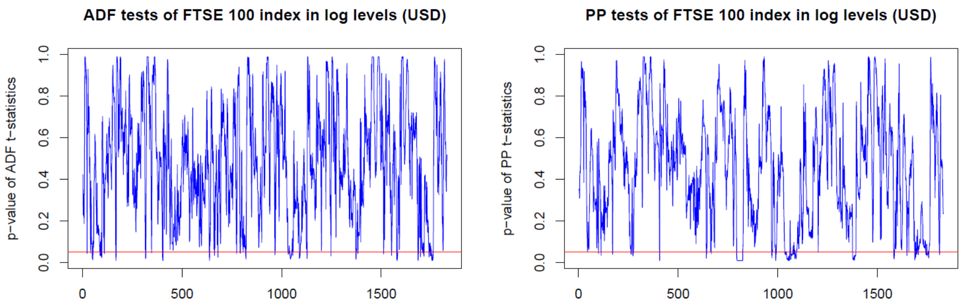


(b) S&P 500 index in log level (GBP)

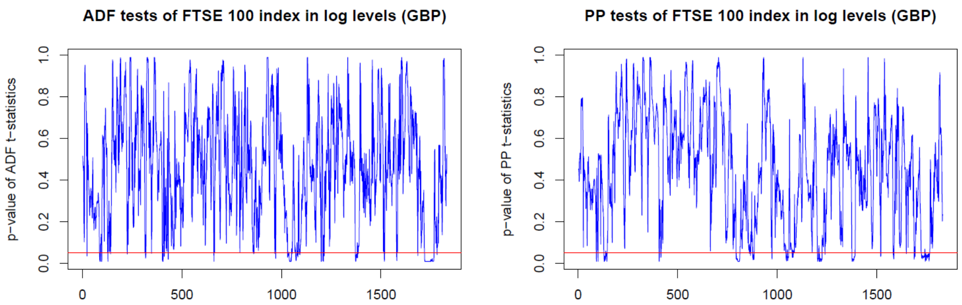


(c) S&P 500 index in log level (EUR)

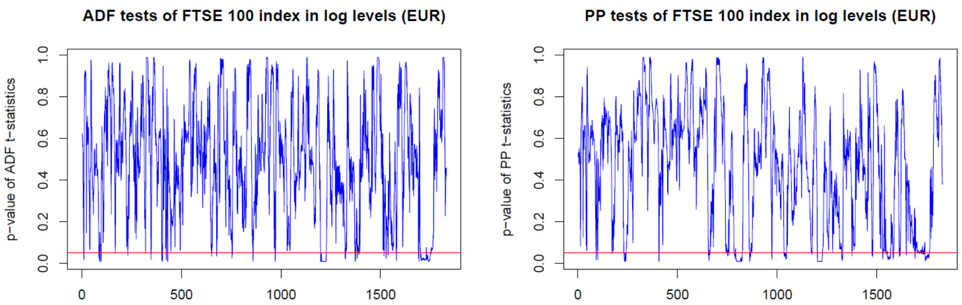
Fig. A.1. p-values from dynamic ADF and PP unit root tests of the S&P 500 index based on USD, GBP and EUR respectively, in log levels. The red line indicates 5% statistical significance level.



(a) FTSE 100 index in log level (USD)

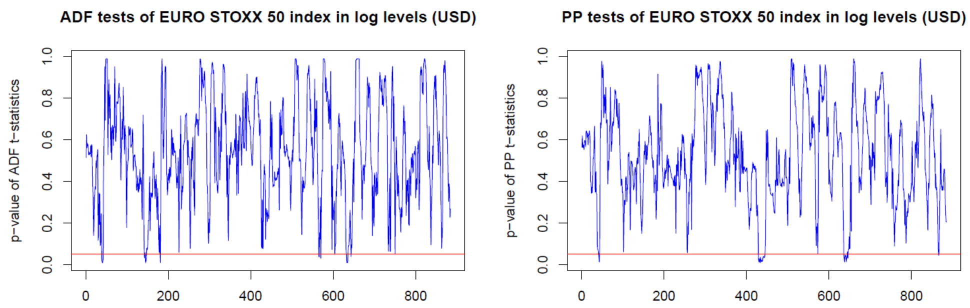


(b) FTSE 100 index in log level (GBP)

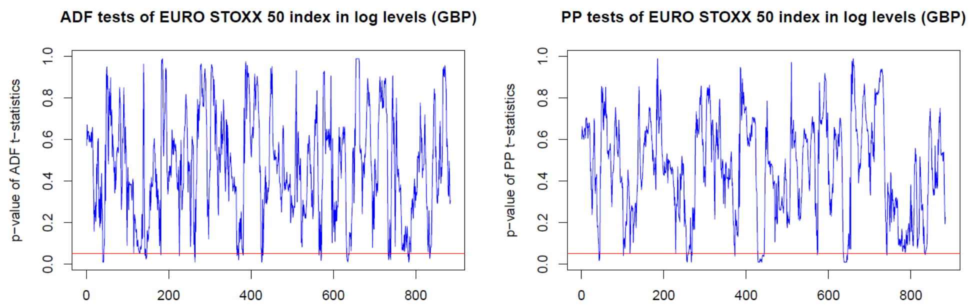


(c) FTSE 100 index in log level (EUR)

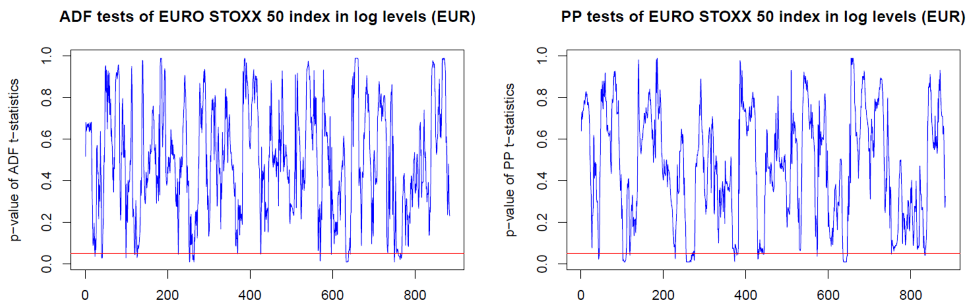
Fig. A.2. p-values from dynamic ADF and PP unit root tests of the FTSE 100 index based on USD, GBP and EUR respectively, in log levels. The red line indicates 5% statistical significance level.



(a) EURO STOXX 50 index in log level (USD)



(b) EURO STOXX 50 index in log level (GBP)



(c) EURO STOXX 50 index in log level (EUR)

Fig. A.3. p-values from dynamic ADF and PP unit root tests of the EURO STOXX 50 index based on USD, GBP and EUR respectively, in log levels. The red line indicates 5% statistical significance level.

Appendix B

B.1 Unit Root Tests for 46 Stock Market Indices

Table B.1. ADF and PP unit root tests of stock price indices.

Country	Log level				1st difference			
	With trend		Without trend		With trend		Without trend	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
CAN	-2.367	-2.526	-2.372	-2.533	-16.618∗	-25.065∗	-16.632∗	-25.086∗
US	-2.195	-2.164	-0.264	-0.302	-16.038∗	-24.933∗	-15.978∗	-24.866∗
AUS	-1.873	-2.102	-2.083	-2.207	-15.671∗	-23.493∗	-15.643∗	-23.479∗
BEL	-1.939	-1.999	-2.129	-2.175	-15.462∗	-23.538∗	-15.417∗	-23.505∗
DEN	-2.019	-2.207	-0.760	-0.943	-15.595∗	-24.716∗	-15.587∗	-24.719∗
FIN	-1.614	-1.794	-1.810	-1.949	-16.38∗	-24.516∗	-16.361∗	-24.51∗
FRA	-2.224	-2.297	-2.381	-2.427	-16.427∗	-24.688∗	-16.412∗	-24.676∗
GER	-2.361	-2.515	-1.606	-1.741	-15.479∗	-24.343∗	-15.484∗	-24.356∗
IRE	-1.880	-1.925	-1.868	-1.935	-16.615∗	-24.294∗	-16.419∗	-24.139∗
ISR	-2.358	-2.529	-1.832	-1.940	-17.250∗	-23.904∗	-17.265∗	-23.925∗
ITA	-2.112	-2.199	-2.153	-2.160	-15.710∗	-23.437∗	-15.685∗	-23.421∗
NETH	-2.076	-2.163	-2.163	-2.249	-15.523∗	-23.209∗	-15.502∗	-23.2∗
NOR	-2.779	-2.855	-1.345	-1.359	-16.679∗	-22.708∗	-16.688∗	-22.723∗
POR	-2.270	-2.470	-1.372	-1.398	-15.658∗	-22.964∗	-15.669∗	-22.981∗
SPA	-2.392	-2.593	-2.069	-2.161	-16.339∗	-24.83∗	-16.343∗	-24.841∗
SWD	-2.271	-2.373	-1.823	-1.921	-16.821∗	-25.338∗	-16.827∗	-25.351∗
SWI	-2.099	-2.267	-1.126	-1.300	-16.091∗	-27.651∗	-16.086∗	-27.649∗
UK	-2.144	-2.180	-2.179	-2.215	-16.913∗	-25.919∗	-16.910∗	-25.92∗
AUST	-2.272	-2.397	-2.274	-2.399	-15.912∗	-24.46∗	-15.927∗	-24.482∗
HK	-2.697	-2.875	-2.524	-2.670	-15.331∗	-23.119∗	-15.342∗	-23.139∗
JAP	-2.486	-2.573	-1.251	-1.318	-15.787∗	-24.421∗	-15.746∗	-24.38∗
NZ	-1.997	-2.043	-1.192	-1.282	-15.520∗	-23.232∗	-15.467∗	-23.197∗
SIN	-1.992	-2.173	-1.944	-2.115	-13.632∗	-21.624∗	-13.645∗	-21.642∗
BRA	-2.508	-2.744	-1.561	-1.798	-15.394∗	-25.199∗	-15.388∗	-25.198∗
CHI	-1.819	-1.922	-1.877	-1.979	-16.831∗	-25.741∗	-16.834∗	-25.747∗
COL	-1.272	-1.435	-0.946	-1.136	-14.925∗	-24.534∗	-14.898∗	-24.517∗
MEX	-2.252	-2.472	-2.222	-2.427	-15.581∗	-26.242∗	-15.595∗	-26.264∗
PER	-1.880	-2.041	-1.779	-1.940	-13.695∗	-20.642∗	-13.699∗	-20.651∗
CR	-2.631	-2.816	-1.771	-1.868	-14.555∗	-21.780∗	-14.566∗	-21.798∗
EGY	-2.189	-2.384	-1.743	-1.916	-15.792∗	-24.150∗	-15.804∗	-24.17∗
GRE	-1.583	-1.716	-1.481	-1.478	-14.858∗	-22.023∗	-14.837∗	-22.016∗
HUN	-2.003	-2.150	-2.180	-2.308	-15.390∗	-22.401∗	-15.371∗	-22.395∗
POL	-2.010	-2.260	-2.071	-2.294	-15.629∗	-24.139∗	-15.628∗	-24.151∗
QAT	-1.950	-2.102	-1.826	-1.746	-15.908∗	-23.197∗	-15.880∗	-23.18∗
RUS	-2.173	-2.368	-1.902	-2.102	-15.167∗	-22.548∗	-15.181∗	-22.567∗
SA	-2.408	-2.551	-2.369	-2.511	-16.738∗	-25.47∗	-16.752∗	-25.492∗
TUR	-2.455	-2.656	-2.369	-2.577	-15.281∗	-23.837∗	-15.291∗	-23.85∗
UAE	-1.402	-1.532	-1.147	-1.216	-16.413∗	-23.259∗	-16.427∗	-23.277∗
IND	-2.390	-2.576	-2.098	-2.275	-13.768∗	-21.746∗	-13.778∗	-21.763∗
INDO	-1.664	-1.893	-1.687	-1.691	-15.357∗	-24.287∗	-15.361∗	-24.294∗
KOR	-2.393	-2.449	-2.117	-2.163	-15.465∗	-23.431∗	-15.478∗	-23.45∗
MAL	-1.422	-1.482	-1.727	-1.764	-15.58∗	-22.237∗	-15.555∗	-22.217∗
PAK	-1.558	-1.586	-0.064	-0.212	-13.797∗	-20.369∗	-13.723∗	-20.337∗
PHI	-1.529	-1.711	-1.035	-1.087	-15.872∗	-24.306∗	-15.884∗	-24.323∗
TW	-2.112	-2.462	-1.585	-1.898	-14.884∗	-23.883∗	-14.887∗	-23.894∗
THA	-1.582	-1.807	-1.341	-1.467	-14.692∗	-22.808∗	-14.700∗	-22.818∗

Note: ∗ indicates significance at the 1% level. Tests for prices in level use a constant but not a time trend. Tests for first differences are performed with neither intercept nor linear trend for the ADF and PP test. MacKinnon (1996) critical values for ADF and PP tests: -3.43 (1%) and -2.86 (5%) for constant and -3.96 (1%) and -3.41 (5%) for constant and linear trend.

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